# Error reduction methods for local maximum filtering

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## Abstract

*Tree crown recognition using high spatial resolution remotely sensed imagery provides useful information relating the number and distribution of trees in a landscape. A common technique used to identify tree locations uses a local maximum (LM) filter with a static-sized moving window. LM techniques operate on the assumption that high local radiance values represent the centroid of a tree crown.*

*While success has been found using LM techniques various authors have noted the introduction of error through the inclusion of falsely identified trees. Missing trees, or omission error, are primarily the result of too coarse an image spatial resolution (in relation to the size of the trees present). Falsely indicated trees (commission error) may be removed through image processing post-LM filtering.*

*In this paper we present a variety of techniques for addressing commission error when applying a LM technique. Methods exploiting spatial and spectral information are applied. The best results, where the number of correct trees is high with few false positives, are found for a spatial filter applied to LM generated within variable window sized as suggested by image spatial structure.*

## Introduction

Individual trees may be discerned, in medium to dense forested areas, on high spatial resolution imagery as regions of high reflectance. The spatial structure of this reflectance, for conifers, results in a local maximum (LM) value found at, or near, the centre of trees. The structure of this reflectance is related to the contrast between pixels representative of trees and the relative brightness of the background material present. In LM filtering, a window is passed over all pixels in an image to determine if a given pixel is of higher reflectance than all other pixels within the window (Dralle and Rudemo, 1997). Pixels identified as the largest digital number within the window are noted as tree locations. When a window of a fixed size is passed over an image it does not account for the presence of trees with different crown sizes, i.e., static sized windows do not take into account the object-resolution relationship that exists between the trees (objects) and the image spatial resolution. The concept of H-resolution, posited by Strahler et al. (1986), presents the relationship between image spatial resolution and image object representation in terms of variance. An H-resolution pixel is spectrally representative of a single object (e.g. tree crown), with a number of similar pixels composing the individual object. As a result, the ability to isolate trees with an LM filter requires an image spatial resolution that is finer than the mean crown size of trees present.

The image spatial resolution necessary for locating stems on digital remotely sensed image data will vary based upon the relationship between the spatial resolution and the tree crown size distribution. In this study, the key crown size threshold for successful identification using LM filters is at 1.5 m crown radius. Trees smaller than this threshold may be successfully located, but at a lower rate of success. These generalizations are applicable for the object-resolution relationship present between the 1 m spatial resolution image data and the unique field data under consideration. These results may influence the desired image spatial resolution of subsequent studies of coniferous forests based upon knowledge of the mean tree size distributions under consideration.

Observation of changing omission and commission errors as a function of crown radii provides an indication of the relation between tree size and image resolution required to resolve individual trees with a LM filter. The distribution of the error by tree size is important as the large trees account for a greater proportion of the stand

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basal area than the smaller trees. An investigation of the success of tree identification by tree crown radius demonstrates the relationship between image spatial resolution and LM filtering success. At an image spatial resolution of 1 m, a tree crown radius of 1.5 m appears to be the minimum size for reliable identification of tree locations using LM filtering (Wulder, et al., 2000).

At the 1 m spatial resolution, an object-resolution exists which precludes the locating of smaller trees with LM filters. Yet, if the larger trees in the stand are consistently located, it may be possible to account for most of the stand basal area. Wulder, et al., (2000) demonstrated that commission error resulted in the over estimation of basal area. In some cases it is illustrated that reducing commision error may come at the cost of increasing omission error. The increase in omission error is rationalized as the trees that are "lost" with decreased commision are usually small and accounting for a small amount of stand basal area. The trade-off between total proportion of trees correct and the level of commission error allows the user to determine which is more important based upon the intended use of the LM filter-generated tree locations. The presentation of a process to estimate basal area from the LM filter-generated tree locations demonstrated that slightly lower proportions of successful stem identification may be quite acceptable as the majority of basal area is accounted for by large trees, and achieving a minimum of commission error is more important.

As indicated, omission error with the LM technique is largely a function of image resolution. Additional tree detection errors may arise through factors such as close proximity of neighboring trees, trees being located under other trees, trees found in shadows, or trees having low spectral contrast with respect to the understorey vegetation. As a result, a primary aim when applying LM filters is to maximize the number of legitimate trees found while also minimizing the amount of pixels falsely identified as tree locations. This paper focuses upon minimizing the commision error, or false positives, identified using an LM filter. To reduce the commision error related to LM filtering additional spectral and spatial information is applied. To reduce commision error we apply and observe the consequences of:

- variable window sizes,
- a spectral threshold and local variance within LM window,
- a spatial dependence threshold, and
- LM filtering of spatial dependence data.

The results of processing with the error reduction methods is compared to benchmark fixed window LM processing with no error reduction applied.

## Methods

### *Study area*

The Greater Victoria Watershed is located at 48° 23' latitude and 123° 41' longitude, which is northwest of Victoria, British Columbia. Within this watershed, a 0.72-ha study area with little topographic variability, composed of a 40-year-old plantation and a 150-year-old naturally regenerating mature stand (GVWD 1991) was selected. The plantation (planted in 1965 and thinned in 1975) is composed of trees ranging in height from 8.6 to 25 m and is a mixture of Douglas-fir (*Pseudotsuga menziesii*) and western redcedar (*Thuja plicata*), while the mature stand contains trees from 140 to 250 years of age ranging in height from 20 to 70 m, and is dominated by Douglas-fir. Also present in the study site is a dense layer of understorey consisting of hemlock (*Tsuga heterophylla*), some red alder (*Alnus rubra*), salal (*Gaultheria shallon*), sword fern (*Polystichum munitum*), Oregon grape (*Mahonia nervosa*) and Oregon beaked moss (*Kindbergia oregana*).

### *Field data*

The 0.72-ha study area was partitioned into 72 grid cells of 10 m by 10 m within which all trees were measured and located to 0.1 m of precision to allow for the creation of a stem map. In total 209 trees were located with 159 trees in the plantation stand and 50 trees in the mature stand. As part of the field work for Hay and Niemann (1994), crown radius, diameter at breast height (DBH), species type, tree height at crown apex, and height at maximum crown radius were measured.

### *Image data*

The second generation Multi-detector Electro-optical Imaging Sensor (MEIS-II) (Till et al., 1983) was flown at an altitude of 1428 m over the study site at 11:30 hr PST on September 2$^{nd}$, 1993 during the first field campaign of the SEIDAM (System of Experts for Intelligent Data Management) project (Goodenough et al., 1994). The resulting ground pixel size is 1 m, with all images resampled to 720 pixels across track. The raw data were geometrically corrected using British Columbia Ministry of Environment Terrain Resource Information Management (TRIM) digital elevation data with a horizontal accuracy of ± 20 m. Solar altitude and azimuth angles at the time of the flight were 52° and 133° respectively.

The MEIS-II is a pushbroom scanner with a temperature stabilized CCD linear array and a spectral range from 380 to 1100 nm. Within the 720 nm spectral range six user-defined, nadir-looking channels may be selected by mounting filters in front of the lens. A panchromatic channel was simulated by averaging the six available channels to summarize the spectral response found over the MEIS-II spectral available range from 432.85 to 847.65 nm. This enables a comparison with the 1 m panchromatic image data available on the IKONOS satellite (with a 450-900 nm panchromatic channel) and forthcoming high spatial resolution satellite sensors (Aplin et al., 1997). Additionally, in previous work it was evident that there was no statistically significant difference between the results LM generated from differing spectral channels (Wulder, et al., 2000).

## *LM filtering procedure*

Individual trees may be discerned, in medium to dense forested areas, on high spatial resolution imagery as regions of high reflectance. The spatial structure of this reflectance, for conifers, results in a local maximum (LM) value found at, or near, the centre of trees. In LM filtering, a window is passed over all pixels in an image to determine if a given pixel is of higher reflectance than all other pixels within the window (Dralle and Rudemo, 1997). Pixels identified as the largest digital number within the window are noted as tree locations.

## *Variable Window Sizes*

### Semivariance

Semivariance is a well-understood and frequently applied image processing technique in remote sensing (Curran and Atkinson, 1998). Semivariograms provide a means of measuring the spatial dependency of continuously varying phenomena. Variable window sizes are suggested for each pixel location based upon an average semivariance range values computed from transects in the eight cardinal directions around each pixel in the image. If there is spatial structure in a given data set, a semivariogram will reveal that semivariance rises until reaching the *sill*, which indicates the maximum variability between pixels. The *range* is the number of lags, or distance, to the sill (Curran and Atkinson, 1998). Therefore, within the range spatial dependence between pixel values is indicated. To minimize the potential effects of image anisotropy, image semivariance is computed for all eight cardinal directions out from the central pixel with the average of the eight results stored in a new image channel. Computing an average range value for each pixel in the image reduces problems which arise when attempting to select a representative single transect origin and angle (Wulder et al., 1998). The eight directional range values are then averaged and written to file as the range to represent that pixel location, this procedure is applied to all pixels inside the image buffer.

The conversion of semivariance ranges to window sizes requires user intervention (Wulder, et al., 2000). The inter-pixel variability is limited at a 1 m spatial resolution, particularly in dense homogenous stands, which results in ranges which characterize the stand spatial dependency rather than that of individual trees. As a result, semivariance range values are consistently scaled to an appropriate window size.

### Slope Breaks

To overcome the need for user intervention in the determination of optimal window size “slope breaks” were calculated. Slope breaks are a simple means of measuring a region of dependence around a pixel. Slope breaks are based upon the assumption that every tree in an image may be a local maximum. For each pixel in the imagery an omni-directional set of transects is analyzed from the central pixel to assess the number of pixels until a minimum radiance value is reached. The slope break may also be described as the first inflection point in the gradient of reflectance around the tree. The inflection point may be considered as an edge location. The mean value of the number of pixels to the slope reversal for all eight cardinal directions is used as a custom window size for that pixel. If a pixel’s radiance is lower than all surrounding pixels, a value of zero is assigned for the window size. The conversion from slope break value for a pixel to customized window size requires no user intervention.

## *Spectral Threshold and Local Variance within LM window*

One of the characteristics of the imagery, and one that affects the number of commission errors encountered in extracting the imagery is the occurrence of random local maximum associations. When this occurs in the imagery the logic of the approach adopted results in a tree top as the main assumption used is that all of the local maxima are tree tops. The reality however is that in many situations where local maxima occur in areas where there are no trees the range in values within the 3X3 evaluation window is quite low. To address these issues, we developed a filter that eliminates candidate LMs which fall below a user specified difference comparing the maximum grey level and the minimum difference within the 3X3 window. User investigation of a series of maximum grey level and minimum difference values is used to determine the most appropriate combination for a particular study location.

### Spatial Dependence (Getis statistic)

In contrast to semivariance, the Getis statistic ($G_i^*$), generates values which relate variations *within* patterns of spatial dependence. Thus, it has the potential to uncover discrete spatial regimes which might be overlooked by existing techniques. Semivariance and $G_i^*$ values are complementary techniques with semivariance computing an indication of a region of pixel similarity and $G_i^*$ results providing the strength of pixel association *within* this region of spatial dependence.

Wulder and Boots (1998) have adapted the Getis statistic for processing remotely sensed imagery. The Getis statistic, $G_i^*$, yields a standardized value which indicates both the degree of autocorrelation in the values of the digital numbers centered on a given pixel and the magnitude of these values in relation to those of the entire image. In consideration of remotely sensed imagery, the $G_i^*$ values measure the extent to which a pixel is surrounded by a cluster of high or low values of a particular variable, such as image digital number (DN) values. Large positive $G_i^*$ values denote a cluster of high DN values; large negative $G_i^*$ values denote a cluster of low DN values. In a high spatial resolution forestry context, $G_i^*$ values indicate the spatial dependence within a tree crown or between shadow elements. High positive values generated from panchromatic image data indicate the presence of a tree object whereas high negative values correspond to a non-tree feature. Accordingly, $G_i^*$ values computed upon near infrared image data may be applied to assist in the screening for false positives generated from the peak radiance filtering routine. Further, as the $G_i^*$ are sensitive to the presence of tree objects, tree locations may be accentuated by the transformation of radiance values to $G_i^*$ values. Processing the transformed $G_i^*$ values for local maxima may allow for improved tree recognition. The ability to extract tree locations from radiance values transformed to $G_i^*$ values is likely highly dependant upon image spatial resolution as the $G_i^*$ values tend to form clusters from the radiance values (Wulder 1999). As a result, processing $G_i^*$ transformed radiance values for LM may only be appropriate on high resolution imagery where many pixels comprise an individual tree crown.

### Spatial data threshold

The spatial dependence threshold is based upon an application of Getis statistic values as a threshold filter. Low $G_i^*$ values indicate a cluster of low DN values; while, high $G_i^*$ values relate clusters of higher DNs. For each pixel that is identified as a potential LM the $G_i^*$ value at that location must be above zero for the LM to pass the threshold filter.

### LM filtering of spatial dependence data

Passing the LM filter directly over the spatial dependence data automatically applies the spatial dependence threshold, as LM are inherently greater then the defined threshold value. Additionally, the $G_i^*$ will have a maxima value at the tree centre while also being surrounded by transformed values extending to the region of local dependence. The extent of the local spatial dependence indicated is variable as related to the size of the tree crowns present. High local $G_i^*$ will indicate centroids of local regions of spatial autocorrelation. The centroids indicated are representative of high panchromatic digital numbers over a region of local dependence.

## Results and Discussion

### Fixed Sized LM Filters with No Error Reduction Applied

Prior to comparison of error reduction methods, a performance benchmark is required. In Table 1 we present the proportion of correct, omitted (missed) , and committed (falsely identified) trees for fixed window LM filtering of image spectral data. (Note, as the omission level is the inverse of the correct value, omission is not noted on each table.) The 3x3 LM filter represents a super-set of all possible LM which may be isolated using a local maximum technique. The 3x3 LM filter finds all local maxima, without regard to any image spatial structure and, as a result, the commission error is generally high. In an operational application, the detailed field data would likely not be present; in that situation, there would be no way to detect false positives, resulting in an over estimate of stems, which emphasizes the need to minimize commission error. In this case the 67% accuracy overall must be taken in the context of 22% commission error, with out the stem map developed for this study a 89% accuracy could be erroneously interpreted. As a result, it is important to consider commission reduction in conjunction with overall numbers of tress correctly identified.

The increase in window size from 3x3 through 5x5 to 7x7 results in increasingly poor results (i.e. more missed trees) for the plantation stand with less of an effect upon the mature stand, indicating that data with resolution higher than 1 m are required for small tree detection. Comparison of the younger plantation stand with the naturally regenerating mature stand, provides an indication of the object-resolution relationship present. The lower success in identifying field located trees in the plantation stand in comparison to the mature stand indicates an inability to discern the smaller trees with 1 m data. The maximum of 67% correct overall may be interpreted as a function of the object-resolution relationship.

With a minimum of 33% of the plantation trees being missed with LM techniques in this study, it appears that 1 m imagery is too coarse for individual tree crown recognition in a Douglas-fir stand with crown radii less that 1.5 m. The mature stand, with an omission level of 20%, appears to have a stand structure that is more appropriate for LM filtering of 1 m spatial resolution imagery. The omission error may be interpreted as being largely a function of the image spatial resolution, whereas the commission error is related to the occurrence of spurious local maxima unrelated to the reflective characteristics of the crown canopy.

Table 1. Results of fixed window size LM filter processing of panchromatic image data.

| Wavelength | PAN (≈448-875 nm) | | |
|---|---|---|---|
| Window Size | 3 | 5 | 7 |
| All (n=209) | | | |
| Correct | 0.67 | 0.50 | 0.30 |
| False Positive | 0.22 | 0.04 | 0.02 |
| Plantation (n=159) | | | |
| Correct | 0.62 | 0.43 | 0.21 |
| False Positive | 0.05 | 0.02 | 0.01 |
| Mature (n=50) | | | |
| Correct | 0.80 | 0.72 | 0.60 |
| False Positive | 0.78 | 0.10 | 0.08 |

## *Variable Window Sizes*

Variable window sizes were applied to the LM filtering process in an attempt to reduce the level of commission error, or false positives, by integrating scene spatial structural information. Semivariance range and slope breaks are computed for each pixel and applied as a unique window size for that location. In the simulated panchromatic channel LM filtering with a variable window size determined by the semivariance method correctly located 64% of the trees in the entire stand, and resulted in a commission error of 19% (Table 2). The lack of a consistent improvement in comparison to the fixed window LM filtering is likely due to the selection of small window sizes from the same image spatial features that results in local maxima being found where no trees are present. Instead of a poorly fit window identifying spurious local maxima and resulting in a high commission level, variable sized windows are being generated for the false-positives. The LM generated from slope breaks have fewer false positives than those from the semivariance range. The measurement of slope breaks from the imagery appears more sensitive to the actual extent of the crown. The semivariance range values, at the study image spatial resolution of 1 m, have a greater likelihood of generating stand level information rather than individual crown information and are thus, less locally adaptive.

The slope break suggested window sized LM filter results illustrate a good relationship between number of trees correctly identified and commission level. For example, the commission for the Mature stand is down from 78% with the fixed 3x3 LM filter to 38% with the same number of trees correctly identified.

Table 2. LM proportion results as computed within variable sized windows suggested from semivariance and local breaks in slope

| Wavelength | PAN (≈448-875 nm) | |
|---|---|---|
| Window Size | SVR | SB |
| All (n=209) | | |
| Correct | 0.64 | 0.62 |
| False Positive | 0.19 | 0.11 |
| Plantation (n=159) | | |
| Correct | 0.60 | 0.56 |
| False Positive | 0.05 | 0.03 |
| Mature (n=50) | | |
| Correct | 0.76 | 0.80 |
| False Positive | 0.64 | 0.38 |

## *Spectral Threshold and Local Variance within LM window*

The application of a spectral threshold and local variance within the LM window resulted in an overall commision error level of 13% (Table 3). The low commision error for the Plantation, of 7%, is expected as the density of the stand in conjunction with the spatial resolution results in many LM hits. More importantly, for the Mature stand, where the opportunity for commision is greater due to the tree size and large spaces between the trees, a false positive rate of 32% is measured. The 32% level of false positives for the LM filter with a threshold and local variance test is an improvement over the use of a fixed 3x3 window with no additional screening, yet the level correct is less than that found for the fixed window analysis. For the mature stand the spectral threshold with the local variance test the commission level is only slightly better than the variable window size dictated from slope breaks, yet the level correct for the is lower than the 80% correct computed for the variable window sizes from slope breaks.

Table 3. Results of the application of a local variance test and threshold value within the LM filter for processing of panchromatic image data.

| Wavelength<br>Window Size | PAN (≈448-875 nm)<br>3x3 |
|---|---|
| All (n=209) | |
| Correct | 0.59 |
| False Positive | 0.13 |
| Plantation (n=159) | |
| Correct | 0.55 |
| False Positive | 0.07 |
| Mature (n=50) | |
| Correct | 0.70 |
| False Positive | 0.32 |

## *Spatial dependence threshold*

The spatial dependence filtering results in a strong reduction in commission error in relation to the unfiltered results (Table 4). A good relationship between number of trees correctly identified is evident for the Mature stand, where correct levels are high and commission is low. Yet, overall the correct level is low, too low to make up for the also low commission level.

The stratification of the results based upon the tree age and size distribution demonstrates superior results for the larger Mature trees over the smaller Plantation trees. Of the larger Mature trees up to 74% are accounted for, while for the smaller Plantation trees, the maximum success rate is 40%. The desired use of the resultant tree locations from the LM filtering will dictate what are acceptable levels of success. For example, this high omission rate may be acceptable if the use of the tree locations is for subsequent signature extraction or basal area estimation. The success of the LM filter based upon $G_i^*$ values to decrease the commission error indicates a potential for directly processing the $G_i^*$ values for local maxima.

Table 4. Variable window size LM filter processing of spectral image data with spatial dependence ($G_i^*$) threshold filter.

| Wavelength | PAN (≈448-875 nm) | |
|---|---|---|
| Window Size | SVR | SB |
| All (n=209) | | |
| Correct | 0.47 | 0.46 |
| False Positive | 0.03 | 0.03 |
| Plantation (n=159) | | |
| Correct | 0.40 | 0.38 |
| False Positive | 0.02 | 0.01 |
| Mature (n=50) | | |
| Correct | 0.70 | 0.74 |
| False Positive | 0.08 | 0.10 |

## *LM filtering of spatial dependence data*

The promising application of $G_i^*$ values as a threshold filter in conjunction with an LM filter indicated the potential for direct processing of the spatial dependency values with a LM filter to isolate individual trees. The result of processing the spatial dependence values with fixed sized LM filters is presented in Table 5. The success rates vary by window size and stand age. The tendency of $G_i^*$ values to represent clusters of similar DN values (Wulder and Boots 1998; Wulder 1999) results in a loss of individual tree location detail, especially in the dense Plantation stand. The clustering effect is clearly demonstrated for 3x3 LM filter on the panchromatic data, illustrated with the result over all age classes with the success level of 16%. An increase in window size results in an improvement in the number of trees correctly identified which relates to the size of the domain of the spatial process. The variable sized windows when applied to the spatial dependence data result in more consistent levels of success (Table 6), with successful identification of trees occurring at a rate of approximately 35%. Successful identification of trees increases as the sizes of the trees increase. The relatively low rate of tree identification is aided by the low amount of commission error. Locations that are identified with the LM filtering of the spatial dependence values are almost invariably trees.

The low, to absent, commission error is related to the manner in which the radiance values are transformed into $G_i^*$ values, with the clusters of high DNs becoming high $G_i^*$ values. The high $G_i^*$ values, accordingly, when processed with a LM filter, act similarly to the $G_i^*$ thresholded results. As with the results for the LM filter suite processed with a $G_i^*$ threshold filter, the desired use of the digitally isolated trees will dictate the success of the LM isolation. The low commission error is of concern if the identified trees are to be utilized for further analysis. For example, the LM located trees may be appropriate for signature development for multispectral classification of the trees. Further, at the 1 m spatial resolution the large trees are being found with the LM filtering method. An analysis of the distribution of the error by the size of the tree is presented in the next section.

Table 5. Fixed window size LM filter processing of spatial dependence ($G_i^*$) transformed image data.

| Wavelength | PAN (≈448-875 nm) | | |
|---|---|---|---|
| Window Size | 3 | 5 | 7 |
| All (n=209) | | | |
| Correct | 0.16 | 0.30 | 0.25 |
| False Positive | 0.00 | 0.00 | 0.00 |
| Plantation (n=159) | | | |
| Correct | 0.25 | 0.19 | 0.14 |
| False Positive | 0.01 | 0.01 | 0.01 |
| Mature (n=50) | | | |
| Correct | 0.66 | 0.64 | 0.60 |
| False Positive | 0.00 | 0.00 | 0.00 |

Table 6. Variable window size LM filter processing of spatial dependence ($G_i^*$) transformed image data.

| Wavelength | PAN (≈448-875 nm) | |
|---|---|---|
| Window Size | SVR | SB |
| All (n=209) | | |
| Correct | 0.35 | 0.34 |
| False Positive | 0.01 | 0.00 |
| Plantation (n=159) | | |
| Correct | 0.25 | 0.24 |
| False Positive | 0.01 | 0.01 |
| Mature (n=50) | | |
| Correct | 0.66 | 0.66 |
| False Positive | 0.00 | 0.00 |

## Conclusions

The efficacy of a given error reduction method must be consider in the context of the number of trees that are correctly identified. When considering the number of trees correctly identified, the size of the trees found in relation to the image spatial resolution must be considered. If small trees, below the range of detection given the spatial resolution available, is beyond the scope of these error reduction methods. Yet, for large trees which are in the realm of delectability omission and commission are more significant. Large omitted trees are unavailable for further analysis, committed trees falsely indicate trees that are not there. Our creation of a detailed stem map allow for the reporting of omission and commission error; without a detailed stem map the committed trees are assume to be incorrectly assumed to be legitimate.

The comparison of error reduction methods must be kept in reference to the comments above. The success, or failure, of a given method is not indicated from commission level alone, the proportion correct must also be considered. The goals of the analysis, that is, what are the stems required for, must also be kept in mind. The error rates found for the Plantation stand are largely a function of the image spatial resolution and little can be done to recover sub-pixel trees. The limits to the plantation results are also at play when interpreting the results over both stands combined. When considering the entire stand, favorable results are found for the variable window size techniques and the threshold/within window variance filters. For the Mature stand, with large crown sizes, encouraging results are found for the spatial dependence filtering of LM generated within windows of sizes suggested by local slope breaks, where correct proportion is high (74%) and the false positive level is low (10%). The results related to the Mature stand indicate that when many pixels comprise an individual crown detection is possible as are useful means for reducing the number of falsely indicated trees.

For future work additional error reduction may be attempted to test species based constraints (such as diameter, size, expected for a given species and age – using *a priori* info), and iterative techniques combining a variety of high and low certainty filters.

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