

# **AUTOMATED METHODS OF TREE BOUNDARY EXTRACTION AND FOLIAGE TRANSPARENCY ESTIMATION FROM DIGITAL IMAGERY**

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## **ABSTRACT**

Foliage transparency in trees is an important indicator for forest health assessment. This paper helps advance transparency measurement research by presenting methods of automatic tree boundary extraction and foliage transparency estimation from digital images taken from the ground of open grown trees.

Extraction of proper boundaries of tree crowns is the initial step in the determination of crown transparency. Subsequent processing methods are reliant on this boundary being correctly delineated. Here, image processing techniques are used to extract tree crown boundaries which are then approximated using spline curves. The resultant splines created by the automatic process can be modified by users in order to represent numerous boundary shapes caused by different crown conditions. In addition, spline coefficients that compactly represent the boundary can be stored for later retrieval, and therefore the system is capable of following changes in each tree over time.

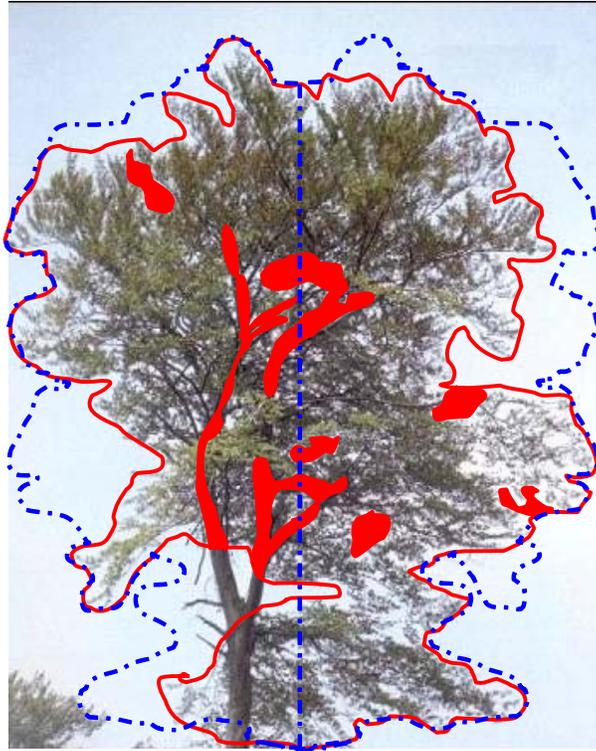
Once proper boundaries are extracted, the foliage transparency is estimated with three different methods. (i) a simple ratio method calculates transparency from a region ratio of foliage area to the inside boundary, (ii) a local method uses a fixed-size window to evaluate transparency for each small region, and (iii) a region tessellation method constructs a triangular mesh using a set of points inside and on the boundary and calculates transparency for each triangular region. While the first method gives us a classical transparency measure, the other methods provide a spatial distribution of foliage transparency. Experimental results show that all three methods provide reliable transparency estimates.

## **INTRODUCTION**

Foliage transparency in trees is an important indicator for forest health assessment. This is evidenced by the collection of this variable, in different forms, under many forest health data collection protocols including the Santiago Declaration of the Montreal Process (Anon., 1995). Foliage transparency is defined by the USDA Forest Service as the amount of skylight visible through the live, normally foliated portion of the crown (USDA Forest Service, 2002). Another variable, crown density, is defined as the amount of crown branches, foliage and reproductive structures that blocks light visibility through the crown. In the procedure for collection there is also a distinction made between the boundary being considered for each of these measures, transparency and density. The boundary for estimating foliage transparency is analogous to a "shrink wrap" of only the leaves. The boundary for estimating crown density is a symmetrical outline of the crown taking the greater distance of the extremities from either side (Figure 1).

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**Figure 1.** Depiction of boundaries and canopy components representing crown transparency (solid red line) and crown density (dashed blue line).

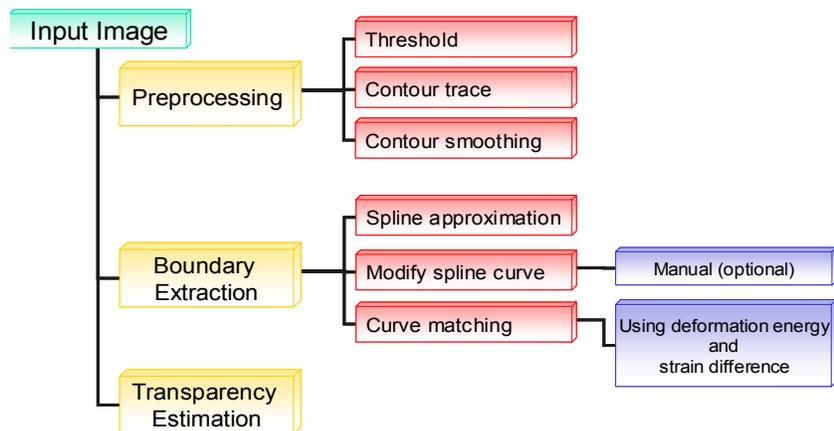
The nature of the transparency indicator and the procedure by which it is collected suffers from subjectivity and potential observer bias (Innes, 1988). This is a great problem when the data are analyzed or used for modeling. There is a need for an objective and repeatable method which can be used for repeated measurements. This study provides a component part towards such a system using digital imaging from the ground.

This paper will describe an automatic process using digital images to create spline curves representing tree crown boundaries. Three methods for evaluating tree crown transparency within these boundaries are presented. Finally, conclusions are drawn and suggestions for future research are put forth.

## DESCRIPTION OF THE METHOD

Digital images of tree crowns are captured from the ground by locating a camera at a distance from the tree base approximately equal to the tree height. This methodology is adapted from the current protocol for transparency estimation set forth in the USDA Forest Service Phase 3 data collection manual (USDA Forest Service, 2002). Figure 1 is an example of a typical image. For this study, primarily open-grown trees are considered in order to minimize foreground and background interference. These other objects create difficulty in the segmentation of the canopy from the rest of the scene.

The process consists of three main steps: 1) image preprocessing, 2) boundary extraction, and 3) transparency estimation (Figure 2). Within these main steps, mathematical operations are used to quantify the features of interest.



**Figure 2.** Diagram of the process for image processing, boundary extraction and matching, and transparency estimation.

### Image Preprocessing

Image preprocessing serves the purpose of determining image space coordinates for boundary representation and segmenting canopy versus background pixels. Otsu's (1979) threshold method is applied to the blue intensity image and serves as an adequate segmentation method for the purpose of transparency evaluation (Mizoue and Inoue, 2001). This is not an exact method, but serves as a close surrogate for segmenting the canopy from the background. Other methods are under investigation by the authors of this study (Clark et al., In Press) for more reliable segmentation methods over a wider range of image conditions. Morphological closing is performed on this thresholded image. Next a distance transform is calculated to provide a gradient around the generalized canopy area. A contour is then determined from the distance transform resulting in a singular external boundary region representing the canopy. This contour is smoothed by interpolation and used in the next spline approximation step.

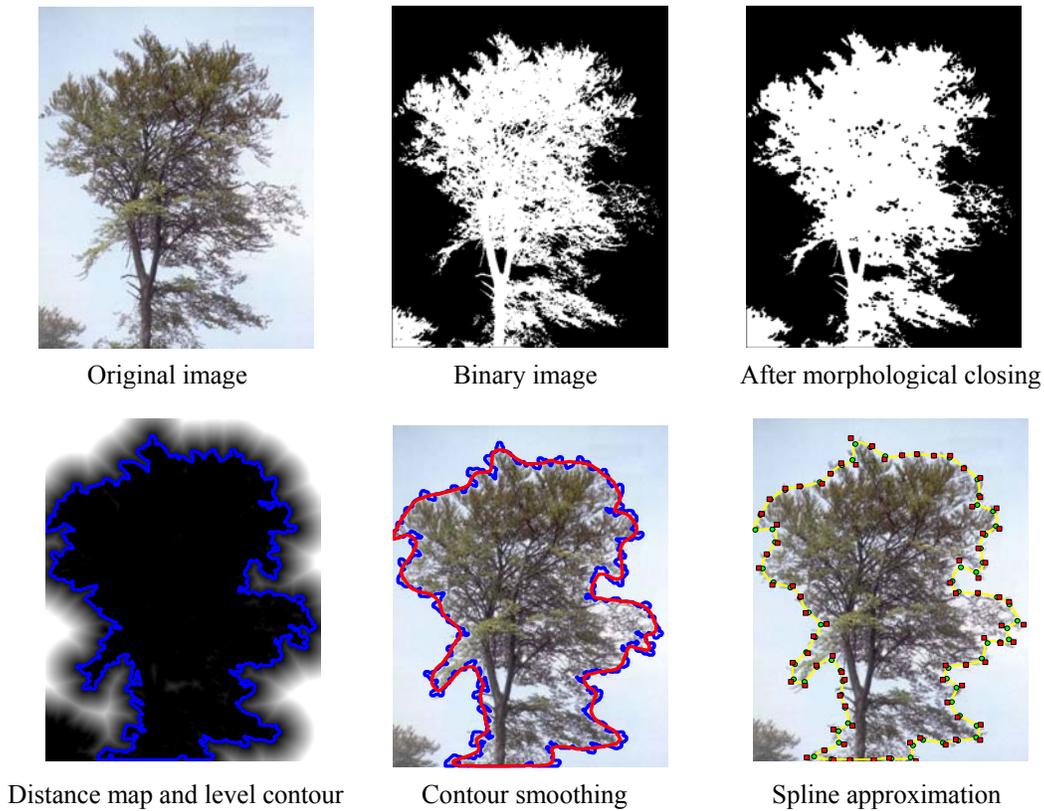
### Spline Creation

A spline representation is used to create a vector representation of the smoothed contour created in the image preprocessing step (Figure 3). This gives us a more generalized crown area under which the transparency is considered. The spline representation is useful for boundary modification and boundary matching. For the purposes of this study, a spline curve is given by:

$$f(t)=[x(t)y(t)]=\sum_{i=0}^{g-n-1} c_i N_i^{n+1}(t), \quad t \in [t_n, t_{g-n}] ,$$

where  $c_i=[c_i^x c_i^y]$  are control points and  $N_i^{n+1}(t)$  is an n-degree B-spline function over the range of  $[t_i, t_{i+n+1}]$  (Wahba, 1990).

As a basis for the function, a set of knots must be selected. There are many ways to do this; however, in this study a minimum number of uniformly distributed knots were initialized. Then fitting errors were calculated and knots were added iteratively where the error exceeded some tolerance. Provision was also made within the computer program for the user to interactively add knots and move control points in order to manipulate the spline to the desired image area.



**Figure 3.** Preprocessing and spline approximation.

### Spline Matching

Extracted crown boundaries may reveal too much detail on tree outlines by showing shapes of every small branches and even leaves. Deciduous and highly transparent trees, in particular, demonstrate a high level of outline complexity. Such a tight boundary may produce a false estimation of transparency. This can be amended by introducing model crown boundaries. A spline curve extracted from the previous section is matched with pre-stored models, and a best matched model is selected as crown boundary of the tree. Matching cost consists of deformation energy and strain energy difference. This section gives a brief explanation of the underlying concept and mathematics. For more details description of the matching procedure, refer to (Lee et al., 2003).

The spline matching starts by finding correspondences between the knot points of two boundary curves. Then, a thin plate spline (TPS) is used to represent coordinate mappings from a point set  $\{\mathbf{v}_i = (x_i, y_i)\}_{i=0}^p$  to its corresponding points  $\{\mathbf{v}'_i = (x'_i, y'_i)\}_{i=0}^p$ . TPS interpolant, denoted by  $f(x, y)$ , has the form (Bookstein, 1989)

$$f(x, y) = \mathbf{a}_1 + \mathbf{a}_x x + \mathbf{a}_y y + \sum_{i=1}^p \mathbf{w}_i U(\|(x_i, y_i) - (x, y)\|),$$

and minimizes the deformation energy that is proportional to

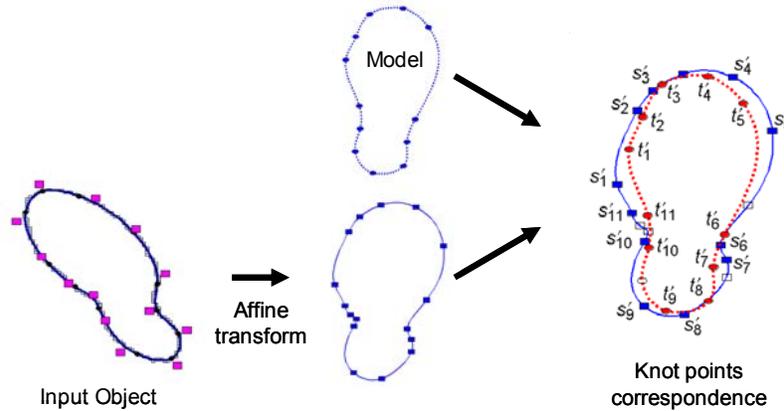
$$I_f \propto \mathbf{w}^T \mathbf{K} \mathbf{w}.$$

The correspondence found yields new ordered knot locations  $\{t'_k\}_{k=1}^{p'}$  and  $\{s'_k\}_{k=1}^{p'}$  such that intervals  $[t'_k, t'_{k+1})$  and  $[s'_k, s'_{k+1})$  represent matching portions of two boundary curves. Strain energy difference measures the geometric dissimilarity between two curves by the squared sum of difference of strain energy. The strain energy for a portion  $[t'_k, t'_{k+1})$  of a curve is defined as

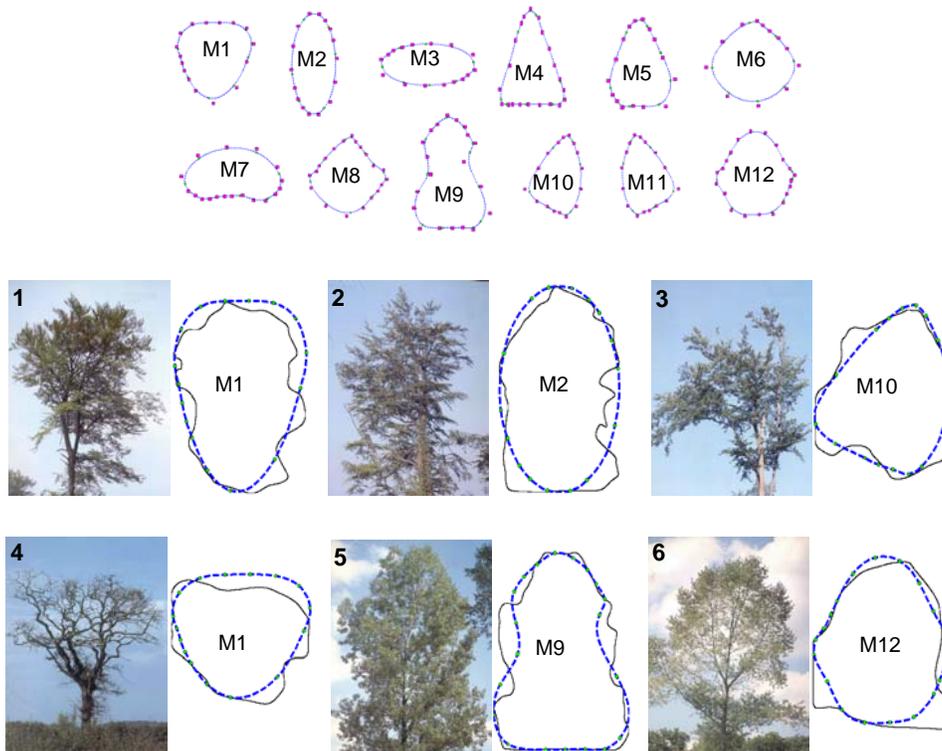
$$\int_{t_i}^{t_{i+1}} (\kappa(t))^2 dt ,$$

where  $\kappa(t)$  denotes curvature at location  $t$ .

Figure 4 shows the spline matching procedure. Initially, affine parameter estimation aligns the input object to a model. Then, a correspondence is searched between the model and the transformed input object as shown in the right of the figure. Deformation energy and strain difference measure the similarity of two spline curves. Figure 5 shows some results of spline matching. Crown models are on the top of the figure followed by input trees and their outlines overlapped with a best matched model.



**Figure 4.** An original spline representation is shown at the left and after affine transformation to approximate characteristics of the model boundary (top center). The overlapping splines on the left depict how the numbers and locations of knot points may not perfectly correspond as well as some deformation error remaining.

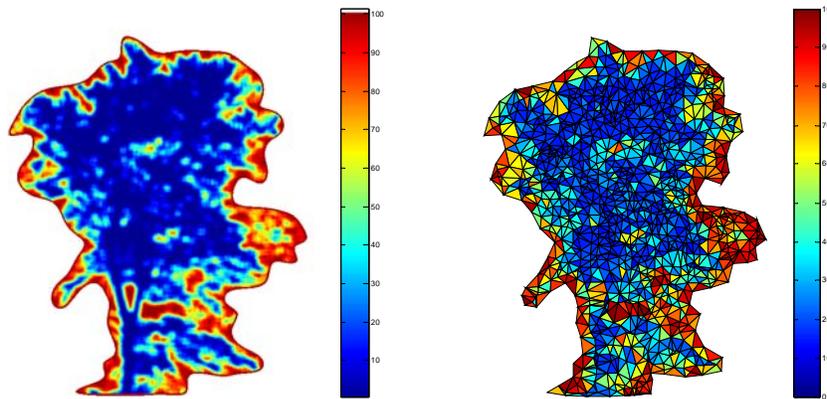


**Figure 5.** Model-based tree boundary extraction. Tree boundaries can be selected from pre-stored models shown at the top. This approach may reduce the false estimation of transparency for deciduous trees with high transparency.

### Transparency Estimation

Three methods are presented for transparency estimation: 1) area ratio, 2) point-wise distribution map, and 3) area-wise distribution map. The area ratio is pixel for pixel ratio of the canopy pixels to the total number of pixels under the bounded area. Figure 6 shows examples of point-wise and region-wise transparency distribution maps. Each pixel of the point-wise distribution map is the area ratio of a fixed-sized square window centered over that pixel. The mean of these pixels is acquired in to give an estimate of transparency. Region-wise distribution maps are the average values under irregular triangular tessellations of the bounded area. All three methods yield similar results as would be expected. Some advantages of these distribution maps would be to look at the dispersion of transparency and the spatial trends over time.

In order to obtain the region-wise distribution map, a watershed transformation is performed on the Gaussian filtered intensity image of the blue color band from the original RGB color image (Figure 7). This technique produces data-driven sized clusters which are located at peaks of image intensity. The values within these watershed regions are “peaks” and the boundaries would be the “tributaries”. So in order to ensure some potential amount of transparency per region, the center points of these clusters are then connected, resulting in a triangulated tessellation of the crown area. Transparency estimates are then calculated for each triangular region. The average of all of these triangular regions gives an estimate of the overall transparency.



**Figure 6.** Point-wise (left) and region-wise (right) distribution maps of foliage transparency.



**Figure 7.** The leftmost frame shows the Gaussian smoothed blue-layer intensity image of a tree crown. The center frame shows the watershed transformation regions derived from the leftmost frame image. The rightmost frame shows the triangulation of the center points of the watershed regions.

## RESULTS

Figure 8 show some preliminary results comparing the three automated methods of transparency estimation with that of a human interpreter. With this limited dataset it appears that the area, point-based, and region-based methods appear to be consistent. It seems that the automated methods are biased with increasing levels of transparency. The cause for this is that, currently, the automated methods include the stem and branch pixels in the estimation of transparency. This is a deviation from the definition of transparency and fits the definition of crown components considered for density estimation. Figure 9 shows that with proper removal of these non-foliar crown components, an estimate is obtained which more closely approaches that of the human investigator.

## CONCLUSIONS

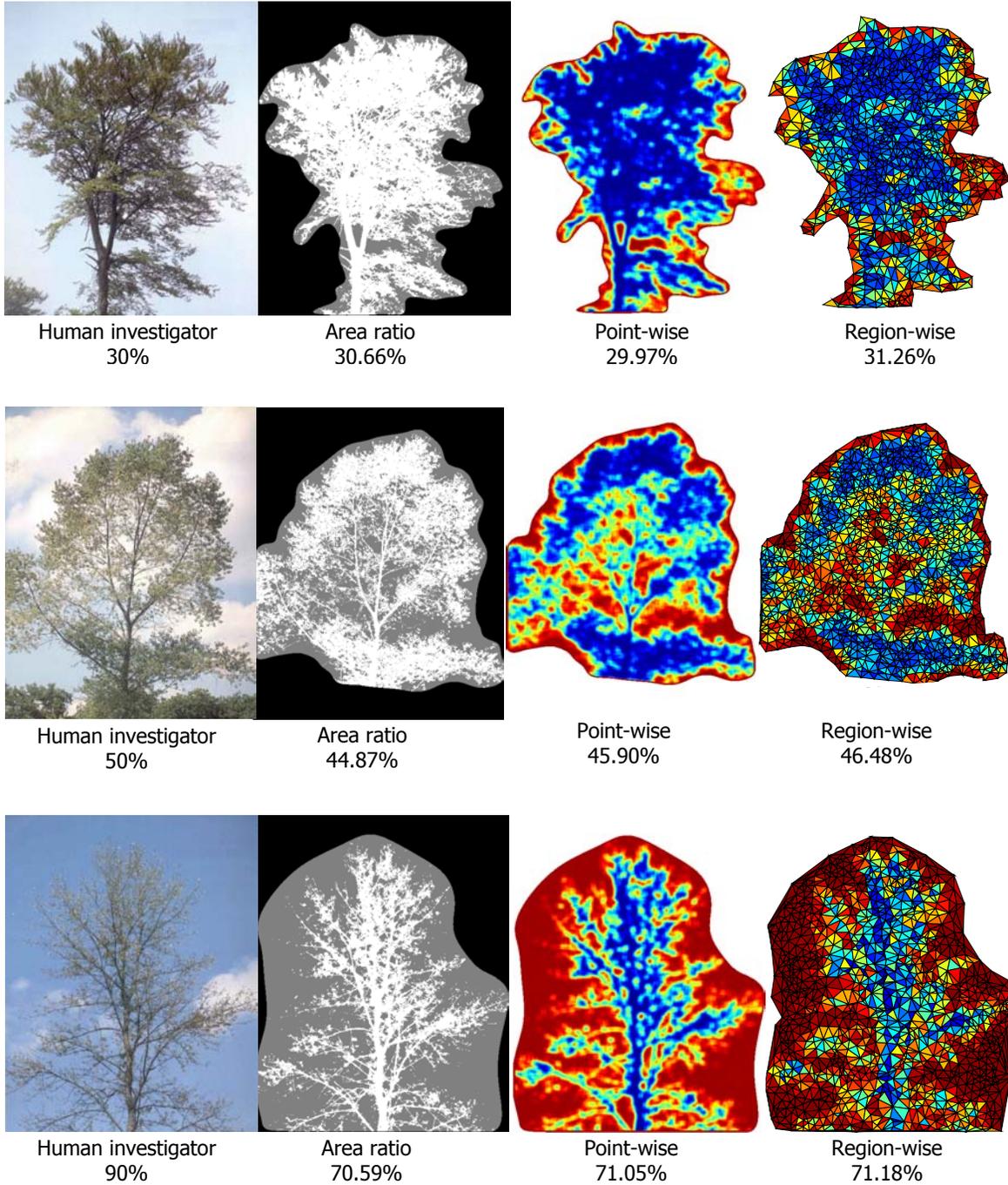
An automated method of tree canopy boundary extraction has been presented. Binary thresholding results in the canopy/non-canopy mask that is used for subsequent transparency analysis. After several more image processing steps are performed, a smooth, raster boundary is produced which simulates a human's perspective of "shrink wrap". B-splines are created as vector representations of crown outlines. This allows the boundaries to be easily modified, if desired, or compared. This will obviate the need for manual matching in the cases where there will be repeated measurements of the same crown over time.

The three methods of transparency estimation: area-ratio, point-wise distribution, and region-wise distribution all produce consistent results for the canopies examined in this study. The slight variation is caused by the level of homogeneity within areas of the distribution methods. The averages of these areas yield results at slightly different resolutions. Area-ratio would be the most closely aligned to human methods by definition. The by-products of the distribution methods are for spatial analysis and analysis at multiple scales. This additional information provided by the distribution maps may prove useful for more in-depth analysis.

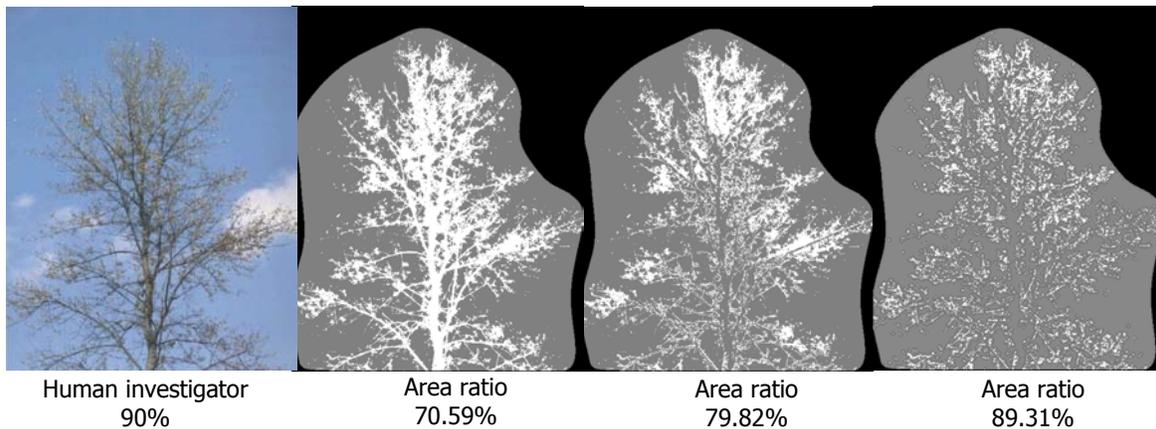
Several issues remain for future research. Methods of automatically determining parameter values for the tightness of the boundary region and appropriate window and region sizes for the two density map methods need to be examined. As transparency estimates depend largely on tree boundary selection, additional rules must be applied and determinations made about the exclusion of sky areas of a certain size, inside of this outer boundary. For instance, due to leaf size and orientation as well as branch morphology, a looser boundary is used on deciduous trees compared with evergreens. This will likely vary by species and image scale. A robust segmentation technique is needed, not only for the initial phase of canopy versus background segmentation, but also for segmentation of leaves from non-foliage canopy structures.

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Photographs reproduced with kind permission of Forest Research, Great Britain. The authors would also like to thank Dr. Christopher Neale for the excellent administration of the conference and proceedings.



**Figure 8.** Results of three levels of transparency showing comparison among human investigator, area ratio, point-wise, and region-wise estimates.



**Figure 9.** Demonstration that removal of woody components from digital images is necessary for proper comparison with human estimates.

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