DELINEATION AND IDENTIFICATION OF INDIVIDUAL TREES IN THE EASTERN DECIDUOUS FOREST

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ABSTRACT

The Ecological Evaluation using Remote Sensing (EERS) group at West Virginia University is studying the health and status of West Virginia's forests using high spatial resolution imagery. Central to our work is a focus on classification and mapping of trees. This paper reports on our initial findings regarding the delineation of individual trees, and discusses future directions we hope to pursue. In a separate paper (Key *et al*, in this volume) we discuss tree species classification using multi-temporal imagery.

Delineation of individual trees in the Eastern Deciduous Forest is challenging due to the variety of scales of tree canopy size, the relatively flat topography of the canopy, and the complex mosaic of the individual crowns. Nevertheless, the shadows between crowns provide a good first cut for identifying tree boundaries. A rank normalization is required to reduce problems due to variable illumination and vignetting. The size of the moving window used in this normalization is crucial in determining the scale of shadows that are enhanced. A window approximately the size of the average tree tends to enhance branching within the crown, whereas a window approximately three times the size of the average tree enhances individual tree crowns. The shadows are, however, in short, separate segments that do not isolate the trees. These segments can be connected by orientation information obtained from a direction of minimum texture algorithm. For each pixel in the image, texture is calculated over narrow groups of pixels (1 pixel wide by 11 long) centered on the pixel of interest. The orientation of these groups is incremented by a small angle until all directions have been tested. The direction with the lowest texture is written out to a new file. A rule-based algorithm is currently being developed to use this information to join shadow segments.

Keywords: tree-boundary, texture, image segmentation, shadows, rank-normalization, texture direction, adaptive filters.

RÉSUMÉ

DÉLIMITATION ET IDENTIFICATION DES ARBRES DANS LES FORÊTS DÉCIDUES DE L'EST DE L'AMÉRIQUE DU NORD

Le groupe sur l'évaluation écologique au moyen de la télédétection (EERS pour Ecological Evaluation using Remote Sensing) de la West Virginia University étudie l'état de santé et la situation générale des forêts de la Virginie-Occidentale à l'aide de l'imagerie spatiale à haute résolution. Les travaux du groupe portent essentiellement sur la classification et la cartographie des arbres. Le présent mémoire fait état des premiers

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résultats portant sur la délimitation des arbres et aborde divers aspects que le groupe compte approfondir. Dans un document distinct (Key et coll., dans ce mémoire), le groupe traite de la classification des espèces d'arbres à l'aide de l'imagerie multitemporelle.

La délimitation des arbres dans les forêts décidues de l'est de l'Amérique du Nord pose des défis en raison de la variété des échelles dans les superficies du couvert, de la topographie relativement plane du couvert et de la mosaïque des houppiers. Néanmoins, les ombres entre les houppiers constituent un premier élément d'importance pour identifier les limites de chaque arbre. Il faut procéder à une normalisation du classement pour réduire les problèmes causés par l'éclairement variable et le vignettage. La dimension de la fenêtre mobile utilisée dans cette normalisation est essentielle pour permettre d'établir l'échelle des ombres qui sont accentuées. Dans une fenêtre dont la dimension approximative correspond à un arbre moyen, les branches sont accentuées par rapport au houppier. Par contre, dans une fenêtre dont la dimension approximative correspond à environ trois fois celle d'un arbre moyen, ce sont les houppiers qui sont accentuées. Toutefois, les ombres constituent des segments distincts qui n'isolent pas les arbres. Ces segments peuvent être connectés au moyen de données d'information obtenues par un algorithme de direction de texture minimale. Pour chaque pixel de l'image, on calcule la texture dans des groupes rapprochés de pixels (1 pixel de large sur 11 pixels de long) centrés sur un pixel repère. L'orientation de ces groupes est incrémentée d'un angle étroit, jusqu'à ce que toutes les directions aient été testées. La direction présentant la plus faible texture est transférée dans un nouveau fichier. Un algorithme basé sur des règles est en cours de développement pour pouvoir utiliser cette information en vue de joindre les segments d'ombre.

INTRODUCTION

Ecologists interested in forest dynamics at the individual tree level are only now beginning to explore the potential uses of high spatial and high spectral resolution remote sensing. However, initial attempts to use such data illustrate the potential. For example, Schlesinger and Gramenopoulos (1996) used high spatial resolution aerial photographic and defense satellite data to test for desertification in the Sahel by examining tree densities in images collected over 51 years. This example is particularly illuminating because it shows that not only is satellite remote sensing capable of examining individual trees, using these data it is possible to test for *change* in densities over time. In this study, no time-trend was observed, suggesting that if it is occurring at all, desertification is slower than previously thought in the Sahel (Rapp 1976, Holcombe 1987, El Moghraby 1987). Of course, an equivalent study could have been carried out on the ground, however, sampling interval, area and sample size would have been limited by practical considerations.

A range of ecological problems become tractable with the possibility of locating and identifying individual trees by remote sensing. At one end of the spectrum is the detection of rare individuals, genotypes, or species. Detection of rare elements in a forest community is important in several kinds of ecological studies. A forest pathologist may have a particular interest in detecting the presence of rare survivors of a disease or insect pest outbreak in order to find resistant individuals. For example, in the eastern deciduous forest field ecologists have observed occasional large American chestnut individuals that have reached reproductive size and age despite exposure to ubiquitous chestnut blight. It may be that 99% of such cases are due to chance escape from the blight, but 1% are due to genetically based resistance. Detection of a large enough sample of reproductive chestnuts to perform genetic screening could be impossible without an extensive search procedure such as that provided by remote sensing.

At the opposite end of the spectrum is the location and identification of individual trees of a common species in a diverse community of similar species. Here, the interest shifts from one of detection of a rare type to defining the individual tree and making relevant measurements on it. The interest may also shift from one of detection to one of examining change over time, both change in individuals (measuring their size changes, detecting their death, assessing their 'health') and in populations (recruitment of new individuals).

In general, assessing attributes that change over time poses the greater technical challenges, however the potential benefits make addressing these challenges worthwhile. One application of multi-temporal remote sensing with excellent payoffs is large-scale population modeling. Minimally, parameterization of a population matrix model of a forest tree species requires repeated censuses of individual trees, including accurate (a) delineation of individuals from the community, (b) classification of individuals to species, (c) size determination, (d) determination of whether an individual is dead or alive at a given point in time, and (e) matching of individual trees across census intervals. All of these steps present some technical challenges for raw data acquisition, image registration and image processing. Even when these challenges have been met, biological assumptions about size-dependent recruitment will be required. Sampling the forest canopy on a 5-year (±2 year) time frame and sampling at the highest possible spatial resolution will help ensure that calculated size transition probabilities and mortality accurately represent the true population changes occurring. Ultimately, the goal of a remote sensing - population modeling marriage would be to assess region-wide status of forest-tree populations on the order of 10^6 - 10^7 trees. From this, it should be possible to overlay demographic patterns and environmental data in a comprehensive GIS database that will provide resource managers with the information needed to judge forest health and the consequences of alternative management strategies.

The Ecological Evaluation using Remote Sensing (EERS) group at West Virginia University is developing the tools to make such studies possible. Central to this work is a focus on classification and mapping of trees. This paper reports on our initial findings regarding the delineation of individual trees and discusses the direction we hope to pursue in future work. In a separate paper (Key *et al*, in this volume) we discuss the value of spectral information versus temporal information in classification of tree species.

IMAGE SEGMENTATION

For our eye-brain vision, the spatial properties of context, pattern and texture are almost certainly a great deal more significant than the spectral property of color. It is therefore intriguing that spatial properties are so rarely drawn upon in remote sensing image analysis. In fact, most image analysis techniques are based on aspatial statistical methods. Nevertheless, the individual tree delineation applications discussed in the previous section clearly require an explicitly spatial approach to image analysis. Image segmentation can be one way of incorporating spatial information, especially if it is carried out prior to classification. In this case, each segment can be classified as a single unit, thus simultaneously enhancing the overall accuracy and reducing the number of classification decisions made, thus reducing classification time (Kettig and Landgrebe, 1976). Segmentation can be purely spectral in nature, such as the ECHO algorithm in which groups of adjacent pixels are tested for spectral homogeneity (Kettig and Landgrebe, 1976). Alternatively, spatial information can be incorporated in the segmentation through attributes such as texture (Ryherd and Woodcock, 1996).

One of the main problems with image segmentation is that there are normally a number of scales in a scene (Woodcock and Strahler, 1987; Strahler *et al.*, 1986). This makes it hard to define definite spatial rules to separate classes. Furthermore, the within class variability of the classes can be greater than the between-class variability. Yet another problem is that if spectral properties are used in image classification, the small number of samples involved make it difficult to exploit class covariance information. This is significant because when there are five or more bands present, much of the class-separability probably derives from differences in class covariance, rather than separation of class means (Lee and Landgrebe, 1993).

Segmentation of individual trees has its own distinct opportunities and problems. In coniferous stands, the tops of the trees are typically the brightest pixels in high spatial resolution images (Gougeon, 1997a). Because of the conical shape of conifers, the bordering shadows are particularly useful in image segmentation . If an image has deep shadows, a threshold can sometimes be applied to separate out the bright pixels as individual trees. Gougeon (1995) has used a rule-based approach for automated tree outline delineation exploiting the local "valleys" of local radiance minima that surround each tree. If trees are further apart, and the ground is illuminated, tree shadow direction can be used to identify structural properties such as stand density (Gougeon, 1997b; St.-Onge and Cavayas, 1997).

Our study area is in the Eastern Deciduous Forest of North America. This forest is very different from the coniferous forests where tree segmentation has been so successful. Firstly, the canopy tends to form a complex mosaic as individual trees exploit available canopy gaps. In some cases we have found branches of different trees intertwined, making delineation of the canopy extent of trees very complex. Furthermore, the size and spacing of trees can be very variable, limiting the spatial properties of size and frequency that can be exploited.

Despite the highly efficient exploitation of canopy gaps, we have found a general tendency for trees to be surrounded by narrow bands of shadow. Unfortunately, however, there are also shadows between the major branches, and in many cases these branches occupy areas of the canopy greater than that of the smaller individual trees. Furthermore, the edges of these shadows tend to be diffuse, and the shadows themselves are not continuous. Although some deciduous species do have a distinct profile, the canopy of the mature Eastern Deciduous Forest tends to be relatively uniform in elevation without the marked variation in height that has proved so useful in the West. Old growth forests are much more structurally diverse, but are relatively rare in these forests. These factors make standard edge detection methods, and general rules about the size and shape of trees, of questionable value.

DATA

Our study site is located in the West Virginia University Forest, a 3,509 hectare research facility on Chestnut Ridge, 15 kilometers east of Morgantown, West Virginia. The Forest lies at an elevation 318-795 meters and is dominated by a diverse mixed mesophytic forest. The site is 100 by 100 meters in size and has been mapped from the ground in great detail. Each tree has been identified, its position surveyed, and the bole size (DBH) and canopy diameter measured. Yellow poplar (*Liriodendron tulipifera*) is the most common species, comprising a little over 50% of the plot. Subsidiary species include red and white oak (*Quercus rubra and Q. alba*) and red maple (*Acer rubrum*).

The site has also been photographed 10 times from the air over the spring, summer and fall of 1997. The photography was acquired with two Nikon 35 mm cameras with color and color and color-infrared film. The photographs were scanned using a flat bed scanner, and then individually geometrically co-registered and, if necessary, mosaicked. The base for this geocoding was a photograph acquired with a large format mapping camera, which has excellent photogrammetric qualities. The nominal pixel size of the co-registered images is 6 centimeters. Although the effective resolution of the images is somewhat coarser, this high resolution provided a method for ensuring the maximum quality in co-registration of the images. Furthermore, for the texture analysis discussed below, the smaller pixel size facilitates a fine resolution of texture angles.

For this paper only the color photography from October 23, 1997 was used. This date was chosen because it combines good spectral separability of the major species, with a moderate sun angle and distinct shadowing around many of the trees. (See Figure 1.)

METHODS AND RESULTS

INITIAL BOUNDARY IDENTIFICATION FROM SHADOW THRESHOLDING

The simplest method of identifying the boundaries of the canopy of individual trees is from the shadows on the periphery of each tree. A single band was created from the three visible bands of the rectified photograph for this analysis of shadows. This new band is termed an illumination/albedo image in that it combines both illumination and overall reflectance variations in the three bands. The illumination/albedo band is produced by calculating the magnitude of the vector represented by the spectral value of each pixel, after the haze component has been removed (Pouch and Campagna, 1990). This is achieved by taking the square root of the sum of the squares of the bands.

The resulting image (Figure 1) has the variations in brightness typical of imagery acquired with devices with a large field of view, and especially non-mapping cameras. Therefore, no one threshold can be applied to this image to isolate shadows over the scene as a whole. Fortunately, this problem can be overcome through a standard procedure of normalizing pixels within a matrix of pixels defined by a moving window. In our case we used a rank normalization. In this procedure the rank of the central pixel, with respect to the pixels in the local window, is returned to the output image. Special procedures have to be applied to deal with pixels on the edges of the image, where the rank is adjusted to take into account the smaller number of pixels in the window.

As a spatial operation, the size of the window relative to the scale of the image objects is crucial in this analysis. For example, a 101 by 101 matrix (approximately 6 meters by 6 meters) is approximately the size of a single tree. Thus, the normalization at this scale is very effective at enhancing the individual branches that make up a tree. A larger window size of 301 by 301 (approximately 18 meters by 18 meters) incorporates several trees in each matrix and thus tends to enhance the more significant shadows associated with the boundaries between trees (Figure 2). This window size is great enough to span canopy gaps from dead trees. Larger windows are greater than the scale of the illumination variations in the image and therefore are less effective at suppressing this problem. A cutoff of rank 6,400 (out of the 90,601 pixels in the 301 by 301 window) was selected as the threshold for the discrimination of shadows in this image (Figure 3). This value was chosen as it gave the best tradeoff of identifying many between-tree shadows, with relatively few between-branch shadows (Figure 4). This image was then converted to a binary file for application to the texture image discussed below.

DIRECTION OF MINIMUM TEXTURE

A major problem with texture analyses is that large window sizes are needed to encompass the broad scale of most spatial phenomena. Unfortunately, such large window sizes tend to have a coarsening effect on the image. Furthermore, large window sizes tend to confuse between and within class texture. Ryherd and Woodcock (1996) used an adaptive filter to overcome this problem. Their procedure is to assign the pixel of interest the lowest of the textures of all the windows that incorporate the pixel of interest. This is in contrast to the typical texture analysis, in which the parameter associated with the window centered over that pixel is automatically used. The assumption with the adaptive filter is that the minimum texture associated with that pixel provides the best estimate of this property. Texture derived with an adaptive filter proved useful in image segmentation, although unfortunately the results tend to be somewhat blocky (Ryherd and Woodcock, 1996).

The direction of minimum texture is an extension of the concept of an adaptive filter. However, as will be shown below, it provides additional information relating to the *orientation* of the texture. The texture used for this analysis is the local variance. The direction of minimum texture is based on a comparison of texture in numerous narrow groups of pixels centered on the class of interest. At set angular increments, a linear arrangement of neighboring pixels is chosen from within a larger group of pixels in a square matrix, by setting the matrix positions that define the angle of interest to a value of one. All other matrix positions are given a value of zero, indicating those pixels are not used in the texture calculation. Figure 5 illustrates three (0°, 22.5° and 45°) of the eight angles that can be obtained with a five by five matrix. Larger kernels allow finer resolution of angular direction. In this study an 11 by 11 matrix was used, identifying texture at a scale of approximately 66 centimeters (11 pixels, each of 6 centimeters). The resulting angles are 9° apart, giving a total of 20 directions. Unlike most texture studies, the magnitude of the texture is not of direct interest in this case. Instead we focus on the orientation of the texture as determined by the direction associated with the minimum texture. This attribute is aligned with subtle linear features such as the boundaries of the canopies of individual trees. When the direction of minimum texture information for the entire image is viewed, very little pattern is evident. However, when only the data from the shadow areas is examined, the trends of the shadows can be identified. Figure 6 shows an enlargement of part of the results for the area covered in Figures 1-4. Each color represents a different angle, as indicated by the color wheel below the figure. The manually digitized outlines of the trees have been overlain on the figure to illustrate how this method can be used to identify the boundaries of the trees. The texture orientation of the shadows allows a linking between isolated shadow segments that potentially can be joined to circumscribe each tree. Most isolated noise can be eliminated because the shadows do not have aligned texture orientation. In only a few cases will shadows between larger branches cause incorrect identification of tree boundaries.

CONCLUSIONS AND FUTURE RESEARCH

The delineation of individual trees in the Eastern Deciduous Forest is particularly challenging due to the relatively flat topography of the mature forest canopy and the complex shape of the mosaic of individual crowns. Nevertheless, shadows identified from rank-normalized images provide an excellent first cut method for identifying the boundaries of trees. The size of the window used in image analysis is crucial in determining the scale of the objects identified. A window size of at least three times the size of the average tree appears to be necessary to ensure that branching is not enhanced at the expense of the discrimination of individual trees.

The direction of minimum texture provides additional information that can be used to connect the isolated segments of the shadows. Such information is important, because the individual crowns are not completely isolated by the shadow analysis procedure. We are currently developing a rule-based method to exploit this information. Individual clumps of adjacent pixels with similar minimum texture directions are grouped, and connected to adjoining clumps or projected to nearby clumps. The potential distance of the projection across non-shadow area is dependent on the length and width of the clump, as well as the degree to which this projection is supported by the direction of minimum texture in the intervening non-shadow region.

In future research we plan to incorporate spectral segmentation in our analysis. In highly diverse forests, many trees can be separated based on spectral differences. It therefore would be appropriate to apply tree segmentation in a sequential, or even iterative fashion, in which a variety of boundary detection methods are incorporated in a single tree segmentation program.

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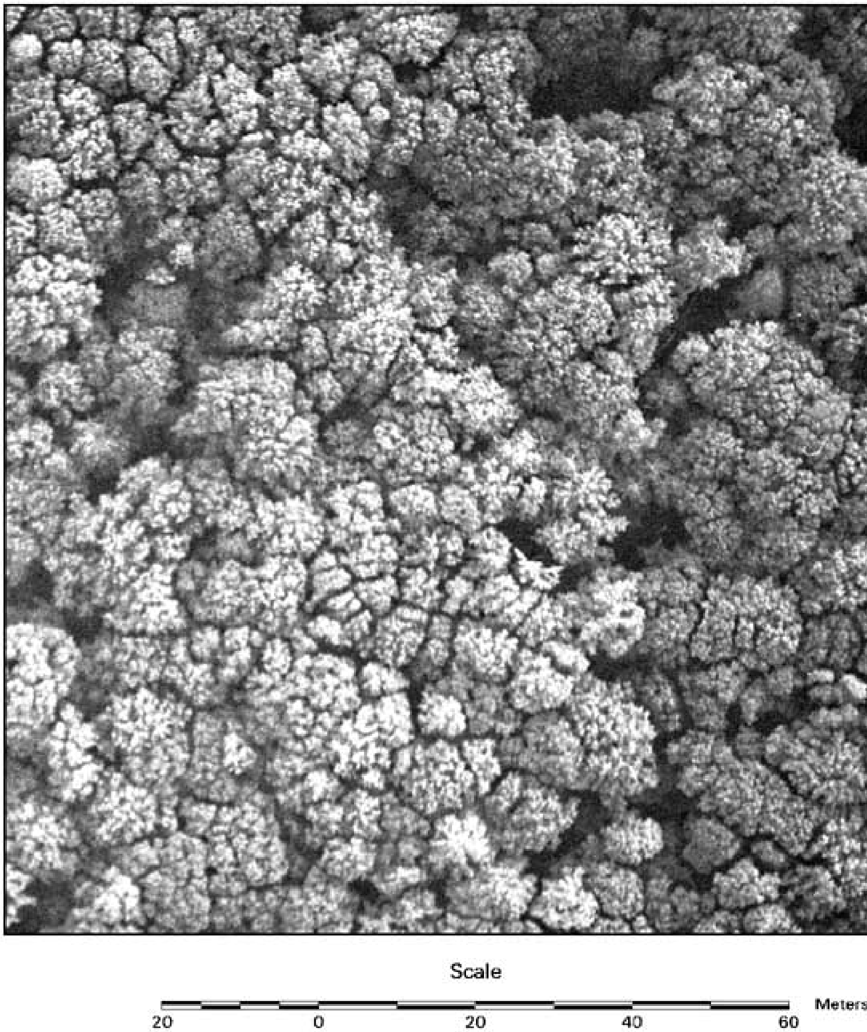

Figure 1. Illumination / Albedo image.

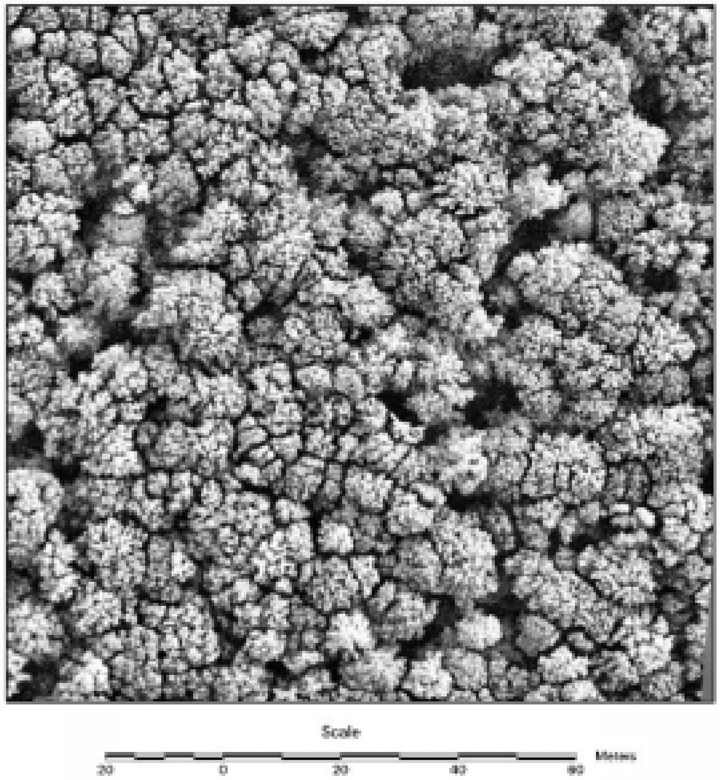

Figure 2. Rank normalized image based on 301 by 301 window.

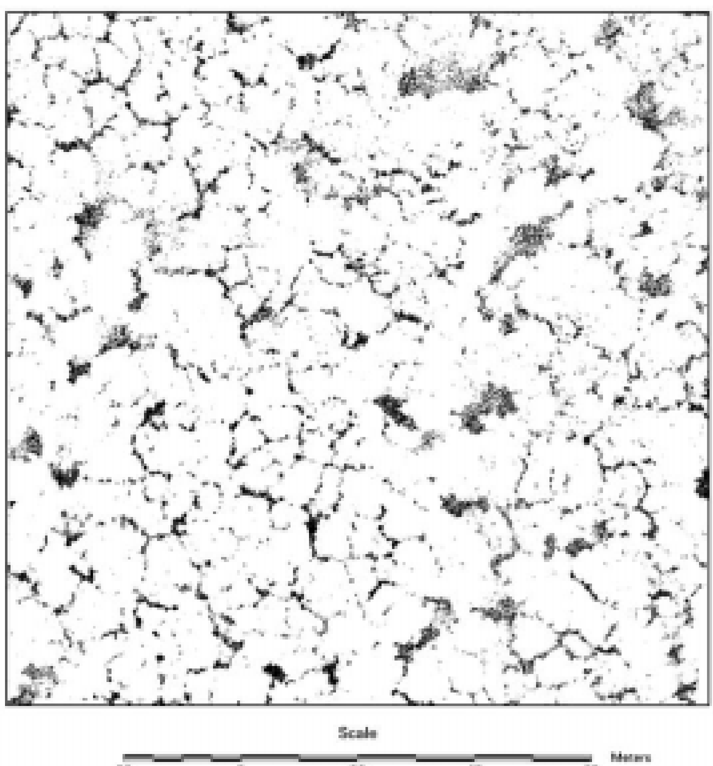

Figure 3. Tree shadows from rank normalized image.

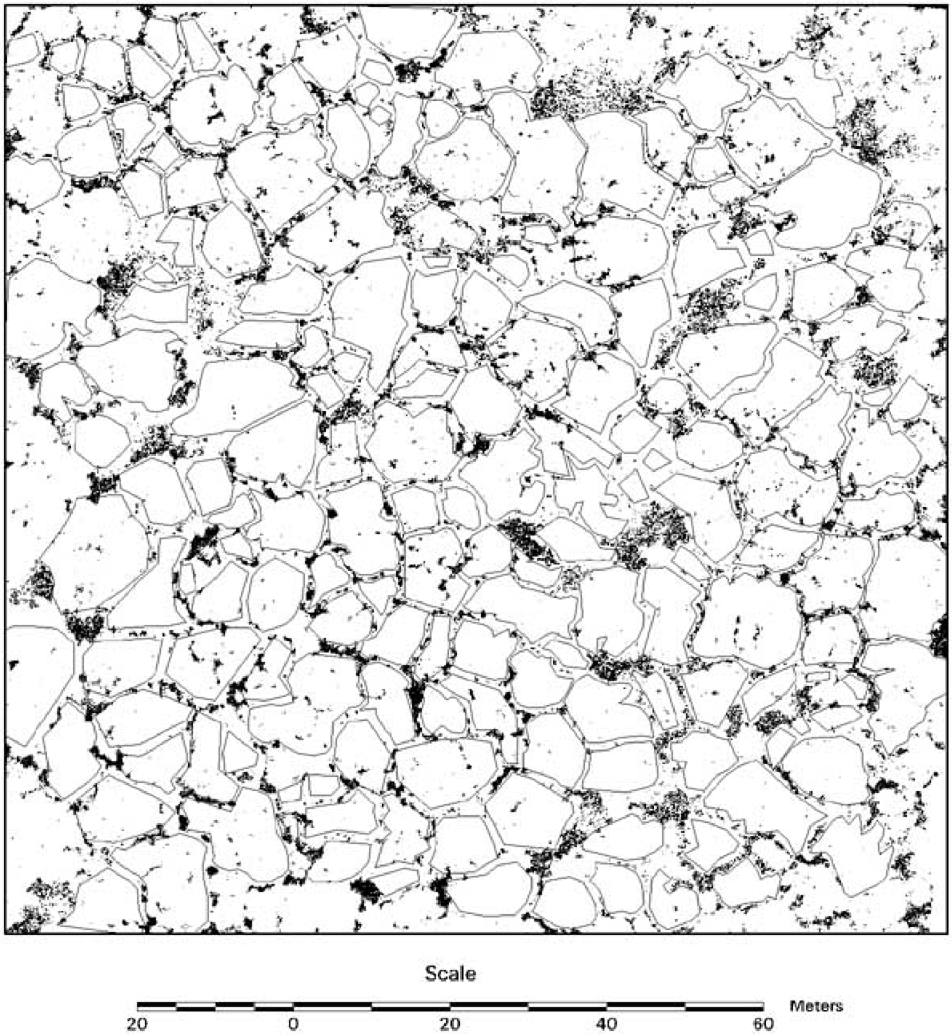

Figure 4. Tree shadows and manually digitized tree boundaries.

0	0	1	0	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0

0° Directional kernel

0	0	0	1	0
0	0	0	1	0
0	0	1	0	0
0	1	0	0	0
0	1	0	0	0

22.5° Directional kernel

0	0	0	0	1
0	0	0	1	0
0	0	1	0	0
0	1	0	0	0
1	0	0	0	0

45° Directional kernel

Figure 5. Directional filters are created by filling a matrix with 0 values in all positions, except along the particular angle which is to be investigated. Larger matrix sizes allow finer gradations in angles.

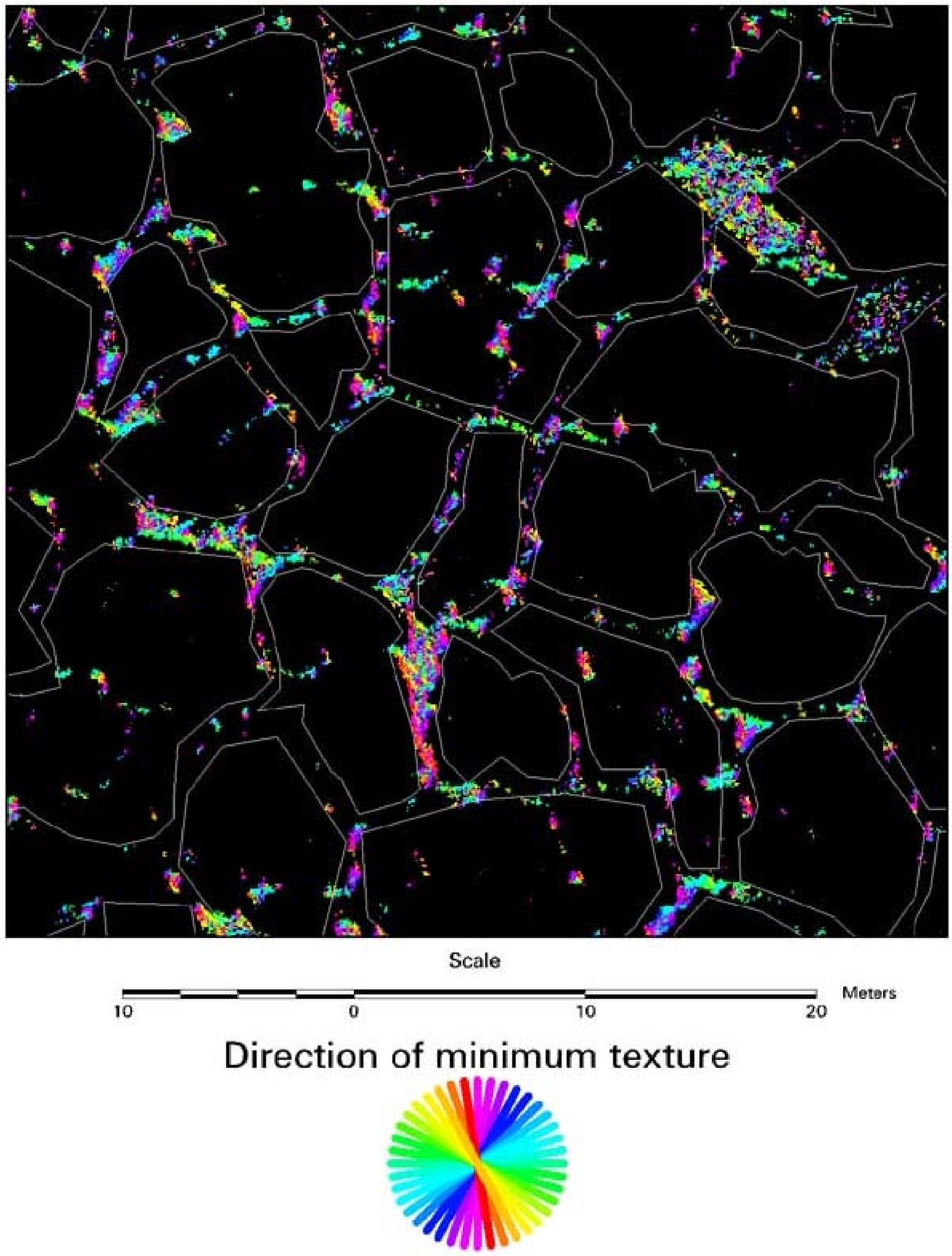

Figure 6. Direction of (11 by 11) minimum texture in shadows. White lines are borders of trees identified through photo-interpretation.