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Classification method of mixed pixels does not affect canopy metrics from digital images of forest overstorey

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ABSTRACT

A great drawback of photographic methods for estimating canopy metrics such as leaf area index (L) and cover has been the tedious and time consuming image processing step and the perceived sensitivity of the results to image processing. This paper describes an automatic method, the 'two-corner method', for detecting homogeneous regions of canopy and sky, and for quantifying the number of mixed pixels in canopy images. Mixed pixels are pixels of intermediate brightness value that do not very obviously belong to either sky or canopy. Four image classification methods were tested for classifying mixed pixels as canopy or sky. When applied to both fisheye and cover images of *Eucalyptus* forest, none of the more complicated classification methods yielded results that greatly differed from a simple global binary threshold classification, even if those metrics were derived from the zenithal distribution of gap fraction or gap size. Increasing photographic exposure by one stop reduced calculated L by 9–12%, but modern digital camera technology makes it much easier to correctly expose fisheye canopy images, either by examining the image histogram in the field or by taking multiple exposures and choosing the best exposures after automatic processing. This study is the first to systematically quantify the number of mixed pixels in canopy images and demonstrated that fisheye images contain more mixed pixels than cover images, and that the number of mixed pixels increases with increasing vegetation cover. In conclusion, the recent advances in digital camera technology, combined with robust and automated image analysis methods, are rapidly bringing the field of photographic analysis of canopy structure to maturity, where the field techniques and image processing aspects of the methodology are no longer significant factors limiting its application by non-experts. In the case of fisheye photography, research is still needed to improve the estimation of L in clumped canopies.

1. Introduction

Ground-based methods for quantifying the distribution and abundance of foliage are essential to monitoring and research programs, and for calibrating models of forest function based on remotely sensed vegetation indices. However, owing to the difficulty of direct measurement of canopy foliage, indirect measurements of leaf area index (L, the one-sided area of foliage per unit ground area, Chen and Black, 1992) and cover (the fraction of ground shaded by the vertical projection tree crowns, Walker and Tunstall, 1981) are frequently employed. Advances in digital photographic technology have led to a resurgence of interest in photography for indirectly quantifying L and cover. Digital cameras have greatly simplified the process of image capture and the instant feedback provided by digital cameras on photographic quality has made obtaining quality images from the field simple and reliable.

However, a significant obstacle to adoption of digital canopy photography remains, that of automation of the analysis of canopy images, in particular the image classification step during image processing. Jonckheere et al. (2004) wrote "The main weakness of methods based on hemispherical photography is due to the post processing step which is generally tedious and time consuming. . .. Consequently, development of software is required to process a series of images and reduce the intervention of the operator". Separating sky pixels from plant pixels is a critical step to obtain accurate gap fraction distributions and gap size distributions (Cescatti, 2007; Jonckheere et al., 2005). Some software still uses manual image classification (e.g. Gap Light Analyzer, Frazer et al., 1999) while commercial software typically has classification algorithms that are commercial-in-confidence and not subject to scrutiny (e.g. WinSCANOPY). A concise history of the development of image classification methods for fisheye images is contained in Wagner and Hagemeier (2006).

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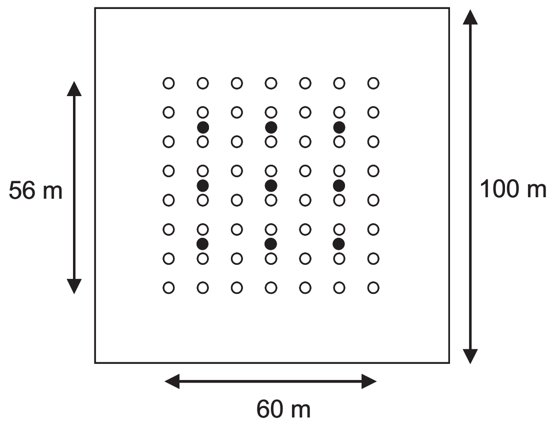

Fig. 1. Layout of the experimental thinning plots at Jarrahdale and the location of cover (open circles) and fisheye (closed circles) image sampling points.

Global binary thresholds can generally successfully classify the darkest plant pixels in homogeneous regions of canopy and the palest sky pixels in homogeneous regions of sky. The main challenge lies in dealing with 'mixed pixels' located around edges where the canopy and sky meet, and also in dealing with luminance variations in the sky. In fisheye images especially, the zenith may be overexposed relative to the horizon resulting in misclassification of brightly lit canopy as sky. In contrast, gaps at the horizon are smaller and darker and contain many mixed pixels, which may be misclassified as canopy (Leblanc et al., 2005). Photographic exposure can further complicate image processing by altering image brightness (Zhang et al., 2005). Proposed alternatives to global binary thresholds include local thresholding methods (Jonckheere et al., 2005; Schwalbe et al., 2006), assigning an intermediate gap faction value to individual pixels based on their digital number (Leblanc et al., 2005; Wagner, 2001) and rescaling image greyscales based on a reference photograph of open sky (Cescatti, 2007). The purpose of this study was to develop a robust automated methodology for classifying both fisheye images and cover images, and to directly compare the impact of several classification methods on canopy metrics including cover, openness and *L*. In the case of fisheye images, their performance was also tested on images captured using different photographic exposures. Finally, the results of cover and fisheye images were compared.

2. Materials and methods

2.1. Image acquisition

In December 2008 both fisheye and cover images were collected in eight experimental plots of jarrah (*Eucalyptus marginata*) forest in Jarrahdale, Western Australia (31°19′S 116°11′E) that had been thinned to different densities or left unthinned. Final basal area of the eight plots ranged from 5 $m^2\,ha^{-1}$ in the most heavily thinned stand to 37 $m^2\,ha^{-1}$ in an unthinned stand. Each 100 m × 100 m plot contained a 60 m × 56 m internal measurement plot within which 56 cover images and nine fisheye images were collected (Fig. 1). Fisheye images were collected just after dawn in uniformly overcast weather and cover images were collected in the morning during either clear sky or overcast conditions. The camera was levelled at each sample point. All images were collected as FINE quality, large size (3872 × 2592) JPEGs with a Nikon D80 DSLR camera set to ISO 400, aperture priority mode and auto-exposure mode. Cover images were obtained with a 50 mm lens set to *f*8, while fisheye images were obtained with a Sigma 4.5 mm circular fisheye lens set to *f*5.6. Three bracketed exposures were collected at each fisheye sampling point: auto-exposure, under-exposed by one stop and under-exposed by two stops. The canopy typically occupies less than half the available pixels in a circular fisheye image (Macfarlane et al., 2007a): in this study each fisheye image contained 3.35 million canopy pixels (diameter of 2065 pixels).

2.2. Image processing

2.2.1. Classification of pixels in homogeneous regions

The first step in image classification was to identify pixels that are unambiguously either sky or canopy. Schwalbe et al. (2006) described a profile analysis to detect homogeneous regions within fisheye images and Jonckheere et al. (2005) used the Ridler cluster method (Ridler and Calvard, 1978) to initially classify pixels as sky or canopy. The software DHP-TRACWin (Leblanc, 2008) requires the user to specify upper and lower threshold limits for homogeneous regions in a semi-automated, interactive process. In this study a histogram-shape based method was used owing to its simplicity and robustness. The method was based on the corner detection method described by Rosin (2001) and Ishida (2004), and could be applied directly to an image's frequency histogram of intensity to calculate two thresholds. In contrast, the Ridler cluster method produces an initial global binary threshold value, not two separate thresholds, and the method of Schwalbe et al. (2006) works directly on the image, not the histogram, and is computationally very intensive. In effect, the method automates the role of the user in DHP-TRACWin and was implemented as follows.

Firstly, the blue channel of the RGB image was selected and a histogram of the digital numbers (DN) was obtained; DN ranges from 0 for black pixels to 255 for white pixels. The blue channel is generally preferred to the grayscale version of the RGB image because the foliage elements have a much lower reflectivity and transmittance in the blue region of the visible electromagnetic spectrum (Leblanc et al., 2005). A mild sharpening filter was applied to the blue channel prior to further processing. In images that contain canopy (<100% gap fraction) there are maxima in the left and right halves of the frequency histogram (Fig. 2a). An algorithm iteratively searches for these maxima to the left and right of the histogram:

$$\mathrm{DN}_{\mathrm{MAX,left}} = \max(\mathrm{DN}_{L1} < \mathrm{DN} < \mathrm{DN}_{L2}) \quad \text{and}$$

$$\mathrm{DN}_{\mathrm{MAX,right}} = \max(\mathrm{DN}_{R1} < \mathrm{DN} < \mathrm{DN}_{R2}).$$

with initial values $\mathrm{DN}_{L1} = 5$, $\mathrm{DN}_{L2} = 55$, $\mathrm{DN}_{R1} = 200$ and $\mathrm{DN}_{R2} = 250$. DN < 5 and DN > 250 were excluded to avoid the detection of spurious maxima resulting from image saturation or underexposure. If one or both of the following criteria is satisfied,

$$\mathrm{DN}_{L2} - \mathrm{DN}_{\mathrm{MAX,left}} \geq 10 \quad \text{or} \quad \mathrm{DN}_{\mathrm{MAX,right}} - \mathrm{DN}_{R1} \geq 10,$$

then that maximum is found and the search ends. If either criterion is not satisfied then the relevant search window is expanded as follows:

$$\mathrm{DN}_{L2} = \mathrm{DN}_{L2} + 25 \quad \text{and/or} \quad \mathrm{DN}_{R1} = \mathrm{DN}_{R1} - 25,$$

and the criteria re-evaluated. The process continues until both criteria are met. These criteria for accepting a maximum prevents very localised, spurious maxima being detected, and ensures that the maxima lie well within the search window. If $\mathrm{DN}_{\mathrm{MAX,left}} = \mathrm{DN}_{\mathrm{MAX,right}}$ then the histogram is unimodal, which indicates an image with little or no foliage cover. Fisheye images are rarely unimodal but empty cover images are common in sparse vegetation.

The second step was to apply the method of Rosin (2001) to detect corners to the left of $\mathrm{DN}_{\mathrm{MAX,right}}$ and to the right of $\mathrm{DN}_{\mathrm{MAX,left}}$. Rosin's method detects the point of maximum curvature on an L-shaped curve by fitting a straight line from the maximum to the last non-empty bin; the corner is the point of maximum deviation