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Master's Thesis of Landscape Architecture

**Correction for light scattering combined with
sub-pixel classification improves estimation of
gap fraction from digital cover photography**

**디지털 사진에서의 빛 산란 보정과 혼합 픽셀
분류 방법으로 개선된 gap fraction 추정**

August, 2016

**Graduate School of
Seoul National University**

**Department of Landscape Architecture and Rural Systems
Engineering, Landscape Architecture Major**

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The Graduate School of Seoul National University
Department of Landscape Architecture and Rural Systems
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Abstract

Digital cover photography (DCP) has emerged as an indirect method to measure gap fraction of vegetation canopies. However, as with other photographic methods, determining camera relative exposure value (REV) and threshold for pixel classification, cause substantial uncertainties in gap fraction estimates. Here we propose a new method to improve the measurement of gap fraction under various solar zenith angles (SZAs), sky conditions, and canopy structures. This method computes gap fractions of ambiguous vegetation or sky pixels using an unsaturated raw image from DCP and a reconstructed sky image from the raw image, thus taking full advantage of the potential of raw image processing. This is combined with pre-classification of pixels that are unambiguously canopy and sky to greatly reduce light scattering effects that are likely to be present within the canopy. To test the sensitivity of the new method, we acquired images at one-hour intervals between 20 and 85° of SZAs under closed, half-closed, and open canopies with REV settings from 0 to -5. The new method showed little variation in gap fractions across the diverse SZAs in closed, half-closed, and open canopies. A perforated panel experiment, which was used to test the accuracy of the estimated gap fractions, confirmed that the new method accurately estimated gap fractions across a range of hole size, gap fractions and SZAs. We conclude that the new method opens new opportunities to estimate gap fractions accurately regardless of solar positions from open to closed canopies, and is a significant advance for accurate and precise monitoring of canopy cover and leaf area index (LAI), and for calibrating and evaluating satellite remote sensing LAI products.

Keywords : *Leaf area index, Gap fraction, Digital cover photography, Light exposure, Remote sensing*

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1. Introduction

Digital cover photography (DCP) is an emerging indirect method to quantify canopy cover and leaf area index (Ryu et al., 2010, 2012, 2014; Macfarlane, 2011; Chianucci and Cutini, 2013; Kimm and Ryu, 2015; Poblete-Echeverría et al., 2015). DCP uses a narrow field of view (FOV: 0–30°), which provides higher image resolution than digital hemispherical photography (FOV: 0–90°) (Pekin and Macfarlane, 2009). DCP-derived gap fraction, the proportion of sky that is unobstructed by canopy in an particular viewing direction (Welles and Cohen, 1996) and leaf area index (LAI) have performed at least as well as other indirect methods in Eucalyptus forest (Macfarlane et al., 2007b), open woodland savanna ecosystem (Ryu et al., 2010; Piayda et al., 2015), and deciduous broadleaf forest (Ryu et al., 2014; Song and Ryu, 2015). However, estimation of the gap fraction of vegetation canopies is sensitive to many factors including solar zenith angles (SZAs), sky heterogeneity, and camera exposure settings (Jonckheere et al., 2005). Many protocols to measure gap fractions using a digital camera require capturing images under restrictive conditions (e.g., overcast sky, clear sky, SZAs >85°) (Breda, 2003; Leblanc et al., 2005; Lang et al., 2010; Macfarlane, 2011; Chianucci et al., 2014; Ryu et al., 2014), and inconsistent protocols for determining the camera relative exposure value (REV) setting and thresholds for classifying pixels into sky and vegetation hamper the comparability of studies (Beckschäfer et al., 2013). To achieve accurate estimates of gap fractions under various sky conditions and vegetation structures, it is imperative to establish a standard protocol for camera REV settings, image processing and analysis.

The camera REV setting is determined by the combination of the camera's shutter speed and f -number, and is an important factor influencing the estimation of canopy gap fraction (Chen et al., 1991; Zhang et al., 2005). In over-exposed images (large REV), digital numbers (DNs) of sky pixels

can be saturated and the boundaries between the sky and canopy can be overexposed, which leads to overestimated gap fraction. On the other hand, in under-exposed images (small negative REV), DNs of canopy pixels are saturated ($DN = 0$) and DNs of small gaps may be too similar to canopy pixels to be correctly classified (Rich, 1990; Schwalbe et al., 2006; Beckschäfer et al., 2013). As a general rule, to obtain a good contrast between canopy and sky pixels, the REV should be decreased as the canopy density increases (Chen et al., 1991; Macfarlane et al., 2000), but this may be insufficient on its own to allow correct classification of all pixels in an image, especially under conditions of varying SZA and heterogeneous sky conditions.

Raw digital image acquisition has clear benefits in quantifying canopy structures (Cescatti, 2007; Lang et al., 2010; Macfarlane et al., 2014) over the Joint Photographic Experts Group (JPEG) image, a standard of file formats and lossy compression technique for color images (Wallace, 1991). Raw DNs collected through the charge-coupled device (CCD) or the complementary metal oxide semiconductor (CMOS) sensor have a linear response to light intensity (Mullikin et al., 1994; Cescatti, 2007; Lang et al., 2010). In contrast, DNs in JPEG format have a non-linear relationship to light intensity that results from the application of automatic gamma corrections, as well as other in-camera processing (Cescatti, 2007). The raw format stores original information in higher bit-depth (10–32 bit) than the JPEG format (8-bit), which distorts the original DNs and reduces the original information content through a lossy compression algorithm (Wallace, 1991; Jonckheere et al., 2005; Verhoeven, 2010; Macfarlane et al., 2014).

Raw image acquisition and processing methods to quantify gap fraction have emerged recently. Lang et al. (2010) described a method involving the reconstruction of a sky image from a single hemispherical raw image taken from the forest floor by combining interpolation with a sky radiance model.

The gap fraction of each pixel was computed as the ratio of the mean of DNs in the canopy image to the mean of DNs in the reconstructed sky image, which Cescatti (2007) termed ‘linear conversion’ based on the linear light response of the camera’s light sensor. Unfortunately, the sky image reconstruction method required manual detection of sky pixels, which limits its application to large numbers of images. The ‘linear conversion method’ was not tested for different REV settings, and will likely be sensitive to light scattering effects by leaves (Kobayashi et al., 2013). For example, the DNs of canopy pixels in digital images are generally greater than zero (black) owing to a combination of lighting conditions and scattering effects, thus taking the ratio of canopy pixel DNs seems likely to overestimate the gap fraction. Although complex methods have been proposed to correct for light scattering in indirect estimates of gap fraction and LAI (Kobayashi et al., 2013), in this study we test a simple method of correcting for scattering (and the fact that leaves are not completely black) when applying the ‘linear conversion’ method by simply identifying pixels that are ‘unambiguously’ canopy (i.e. not sky and not ‘mixed’ pixels) and assigning these pixels a gap fraction of zero.

In a later study, Macfarlane et al. (2014) recommended acquiring raw images with one stop of under-exposure ($REV = -1$), applying a contrast stretch to the blue channel of the red-green-blue combined color digital image, and saving as JPEG format for image analysis. To quantify the gap fraction in the blue channel, a binary pixel classification was used to classify pixels as canopy or sky. The procedure used by Macfarlane et al. (2014) did not fully utilize the raw image information because it only used the raw data as a pre-processing step to reduce sensitivity of results from JPEG images to photographic exposure. In that study it was also observed that the gap fraction in images with small gaps was underestimated compared to images with large gaps despite adjusting for photographic exposure. We hypothesize that applying the ‘linear conversion’ method to

small gaps will reduce the bias in estimated gap fraction that is caused by gap size. It is also unclear whether a small negative REV setting ($REV = -1$) is valid for a range of canopy structures and sky conditions.

We propose a protocol for image acquisition and processing that combines the strengths of previous approaches and fully exploits the potential of raw digital images. We tested the method across various SZAs, REV settings and gap fractions, under both forest canopies and in a controlled experiment with perforated panels. We compared the new method to three previous methods (an adaptation of Lang et al. (2010); Macfarlane (2011); Macfarlane et al. (2014)) to evaluate whether this new method can out-perform those methods. We hypothesize that combining:

- Acquisition of unsaturated raw images
- Raw image processing to obtain DNs that are linearly related to light intensity
- Classification of unambiguous regions of canopy and sky
- Automatic reconstruction of a sky image
- The ‘linear conversion’ method for sub-pixel gap fraction estimation of mixed pixels

Will yield a robust method that largely eliminates biases resulting from photographic exposure, within canopy light scattering and sky heterogeneity.

2. Methods and materials

2.1. Method 1 (sub-pixel raw with scattering correction)

Our proposed protocol for image acquisition and processing, which we henceforth refer to as ‘Method 1’ (Fig. 1), involves the following steps:

- a) Acquire an unsaturated raw image to ensure all DN_s in the image respond linearly to light intensity.
- b) Process the raw image by (1) extracting the blue channel, (2) analyzing the histogram to detect unambiguous sky and vegetation pixels, (3) reconstructing a sky image from the unambiguous sky pixels and (4) removing scattering effects in vegetation by forcing the DN of the unambiguous vegetation pixels to zero.
- c) Compute the sub-pixel gap fraction of the ambiguous pixels (i.e. the mixed pixels) as the ratio of mean in DN_s of the scattering corrected canopy image and the mean in DN_s of the reconstructed sky image.

A detailed explanation of each step of the method follows.

Fig. 1. Overview of the proposed raw image acquisition and processing method.

2.1.1. Acquisition of raw image

The key objective of raw image acquisition is to obtain unsaturated DNs that have a linear response to light intensity (Beckschäfer et al., 2013). Our protocol to achieve this is to capture image under the canopy with a REV of 0 in aperture priority mode then check the histogram in camera display mode to ensure DNs of the blue channel are not saturated. We reduced the REV by adjusting the f -number until there was no evidence of saturation. The first unsaturated image was chosen the best-exposed image as it covers wider range in DNs. To test sensitivity of gap fraction estimates to REV, we collected all unsaturated images up to REV -5 . It is important that REV is set correctly such that the shutter speed is both within the available range supported by the camera and fast enough to freeze foliage movement. Digital single lens reflex (DSLR) cameras typically warn if the required shutter speed is out of range through blinking shutter speed value (Canon and Nikon) in the camera display mode.

2.1.2. Raw image processing

2.1.2.1. Basic raw image processing.

Basic raw image processing involves extracting the Bayer pattern, quantifying the dark current value, and extracting the blue channel raw image with dark current correction (Fig. 1b). We extracted the blue channel, because it is less influenced by exposure changes compared to the red and green channel (Brusa and Bunker, 2014) and has the best contrast between sky and canopy (Frazer et al., 2001; Jonckheere et al., 2005).

We used an open source raw image processing program, dcraw, for the basic raw image processing (Coffin, 2011). We ran dcraw within MATLAB (The MathWorks Inc., Natick, MA, USA) to automate the following raw image processing workflow. First we extracted the raw image Bayer pattern using the ‘ $-i -v$ ’ function to identify the blue channel. Then the dark current value of the blue channel was retrieved using the ‘ $-w -v$ ’

function. The dark current value was confirmed by blocking the camera lens and reading the mean of the image DNs. Lastly we extracted the blue channel from the portable gray map (pgm) format ('-4 -D' function in dcraw to read raw data in 16-bit pgm format) based on the Bayer pattern, and subtracted the dark current value from the blue channel DNs. All subsequent raw image processing was performed on the raw DNs of the 16-bit blue channel after correction for dark current.

Fig. 2. The modified corner detection method of Rosin (2001) applied under clear sky and cloudy conditions. (a) Histogram under clear sky shows an ideal shape with a single peak in the sky region; the straight green line connects the peak frequency DN in the canopy to the last non-empty bin and the blue dot-dashed line connects the peak frequency DN in the sky to the first non-empty bin. The maximum curvature points for vegetation (candc) and sky (skyuc) were determined from the normal line. (b) Histogram under cloudy conditions showed multiple peaks in the sky region; rather than the normal line, skyuc was determined from the first appeared curvature point DN to include all sky pixels. (For interpretation of the references to color in this figure legend and text, the reader is referred to the web version of this article.).

2.1.2.2. Histogram analysis

Schwalbe et al. (2006) first proposed the separation of ‘mixed pixels’ from pixels that are unambiguously either sky or canopy, as a means of improving pixel classification. It is the gap fraction of mixed pixels that leads to the greatest uncertainty in the overall gap fraction of a canopy image. To determine unambiguous vegetation and sky pixels, we adapted the corner detection method of Macfarlane (2011), which was confined to 0–255 DN in JPEG image, for application to the 16-bit blue channel. To detect the point of maximum curvature in an L-shaped (or flipped L-shaped) histogram in the blue channel (Figs. 1 b; 2) we used the corner detection method (Rosin, 2001). We first reduced noise in the histogram by applying a LOESS filter (Cleveland and Devlin, 1988) with the “smooth” function in MATLAB. To identify the maximum curvature points in the downslope curve in vegetation region (candc, green dot in Fig. 2) and upslope curve in sky region (skyuc, blue rectangular in Fig. 2), we developed algorithms to perform the following:

- Detect peak frequency DNs in vegetation (canpk) and in sky (skypk) regions.
- Draw straight lines connecting canpk to the last non-empty bin (green line in Fig. 2), and skypk to the first non-empty bin (blue dot-dashed line in Fig. 2).
- Determine the maximum curvature point as the position where the distance from the straight line normal to the histogram was maximum. When multiple peaks were present in the sky region of the histogram under cloudy conditions (e.g., Fig. 2b), we extracted the first detected DN curvature point (i.e. the lowest DN curvature point) to ensure clear and cloudy sky pixels are all included in the sky reconstruction process.

2.1.2.3. Sky reconstruction

The purpose of sky reconstruction is to recreate an image of the empty sky based on unambiguous sky pixels visible through the canopy. This image is used to calculate the sub-pixel gap fraction of canopy pixels other than those identified as unambiguous canopy pixels. The narrow field of view of DCP allows the user to reconstruct a sky image from a canopy image easier than the wide field of view of digital hemispherical photography. For each image, we first selected the unambiguous sky pixels (i.e., DNs larger than skyuc) then reduced the sky region to ensure pure sky and cloudy pixels are selected; to reduce the sky region we used the ‘imerode’ function in MATLAB with a 5×5 array structure element. Next, we interpolated between unambiguous sky and cloudy pixel DNs using the ‘griddata’ function with the ‘natural’ method in MATLAB. Any non-sky pixels remaining were extrapolated using the ‘inpaint nans’ function with ‘spring’ method (D’Errico, 2005). To test the accuracy of the sky reconstruction method, (1) we took reference sky raw images from clear to cloudy conditions, (2) overlaid canopy images taken under the forest canopy on the sky images and forced the canopy DNs in the sky images to be zero, and then 3) reconstructed the sky images. Finally, the reconstructed sky images were evaluated by comparison with the reference sky raw images (see Section 3.1).

2.1.2.4. Scattering correction

To apply Beer’s Law to compute LAI from gap fraction, the vegetation should be perfectly black (i.e., no scattering). To remove scattering effects by vegetation, we simply forced DNs lower than candc (i.e. unambiguous canopy pixels) to be zero in the processed raw images. Along with the simpler method used to reconstruct the sky image, this is a key difference between the method proposed in this study and the method proposed by Lang et al. (2010), which lacked any correction for light

scattering.

2.1.3. Compute gap fraction

Finally, we computed the gap fraction of the mixed pixels (pixels with DNs between *candc* and *skydc*) as the ratio of the scattering corrected processed raw image DNs to the reconstructed sky image DNs (Fig. 1c). This ‘sub-pixel’ classification method differs from binary classification methods in which each pixel can only have a gap fraction value of 0 or 1. Unambiguous canopy pixels were assigned a gap fraction of zero (see Section 2.1.2.4 above) and unambiguous sky pixels were assigned a gap fraction of one. Finally, gap fraction of an image was computed as the mean in the ratio of the scattering corrected processed raw image DNs to the reconstructed sky image DNs.

2.2. Comparison methods

We compared our proposed method (Method 1) to three other published methods as follows:

2.2.1. Method 2 (Binary JPEG)

The main purpose of Method 2 was to reduce uncertainty in pixel classification by identifying unambiguous canopy and sky pixels and applying pixel threshold only to mixed pixels. It is a binary classification method based on Macfarlane (2011) and involved processing the blue channel of JPEG images collected concurrently with raw images, at a range of exposure values. Pixels that were unambiguously vegetation or sky were classified using the ‘two corner’ method described above (Section 2.1.2.2) and remaining mixed pixels were classified into vegetation and sky by applying the “dual binary threshold” method (Macfarlane, 2011). The gap fraction was quantified from the binary image as the fraction of sky pixels in the image.

2.2.2. Method 3 (Binary raw)

Method 3 was an improvement on Method 2 in that it used raw image processing to reduce the sensitivity of estimated gap fraction to photographic exposure. Method 3 is based on Macfarlane et al. (2014) and also binary classification method that involved processing raw images taken with REV settings of -1 or -2 . The 16-bit blue channel of the raw image had a contrast stretch applied to it using the “imadjust” function in MATLAB with default parameters. The stretched image was converted to 8-bit and a gamma adjustment of 2.2 was applied. The image was then saved as a JPEG, which was processed as for Method 2 above.

2.2.3. Method 4 (Sub-pixel raw with no scattering correction)

Method 4 is a sub-pixel classification method based on Lang et al. (2010), which sought to reduce the errors in gap fraction estimation by taking the ratio of the DNs in the original canopy image to the DNs in a reconstructed sky image. Whereas Lang et al. (2010) used interpolation and a sky radiance model in combination with the original image to reconstruct the sky image, in this study we used the methods described in Section 2.1.2.3 above to reconstruct the sky image. Hence, Method 4 is identical to Method 1, except that no scattering correction (Section 2.1.2.4) was applied, i.e. the gap fraction of unambiguous canopy pixels was not set to zero and their gap fraction was calculated as described in Section 2.1.3 above for mixed pixels.

2.3. Site description

The experimental sites are a building rooftop and closed, half-closed, and open forest canopies at Seoul National University (SNU), located in the west-central portion of Korean peninsula. To avoid shadows from canopies and buildings, we conducted a perforated panel experiment

on the rooftop of the College of Agriculture and Life Sciences building (37.457N, 126.948E). A forest stand is located at the western part of the SNU campus (37.455N, 126.949E). Within the stand, we chose three locations that represent closed, half-closed, and open canopies. In both closed and half-closed canopies, the dominant species was *Zelkova serrata* Makino, and the mean canopy height was approximately 13 m. In the open canopy site, the dominant species was *Acer palmatum*, and the mean canopy height was approximately 9 m.

2.4. Data collection

2.4.1. Forest canopy experiment

To test the sensitivity of estimates of gap fraction from the four methods to REV setting across diverse canopy structures and SZAs, we collected images in closed, half-closed, and open canopies with SZAs between 20 and 85°. Under the closed canopy, a DSLR (Canon EOS 600D) was installed on a tripod 1 m aboveground, pointing towards the zenith. Images were taken at one-hour intervals, between 1400hh and 1900hh on June 23, 2015. Clouds occupied 50% of the field of view (FOV) in images between 1400hh and 1500hh. Under the half-closed and open canopies, each DSLR (Canon EOS 550D for the half-closed canopy, Canon EOS 600D for the open canopy) was installed in a manner similar to that of the closed canopy. Images were taken at one-hour intervals between 0600hh and 1100hh on August 6, 2015. Clouds occupied 20% and 10% of FOV in images at 0900hh and 1100hh, respectively. For all DSLR cameras and forest locations, the lens focal length was set to 55 mm, and aperture priority mode was used, with aperture set to f/18 or f/10 depending on illumination conditions to achieve the desired REV setting. For each hourly observation, we acquired three images at each REV settings from 0 to -5. All images were saved as 18.0 megapixels resolution, in both JPEG (5184 × 3456 pixels) and raw (5202 × 3465 pixels) formats.

2.4.2. Perforated panel experiment

To test the accuracy with which each method quantifies gap fraction, we conducted a controlled experiment using perforated panels on July 4, 2015. We painted three 1.8 m by 0.9 m with 1.5 mm thickness perforated panels with non-glossy black spray to reduce the reflectance of the solar radiation. The factory-specified gap fractions of the three perforated panels were 0.10, 0.33, and 0.38. The perforated panels were placed on top of a $1.8 \times 0.9 \times 1.8$ m iron hexahedral frame. We installed a DSLR (Canon EOS 600D) camera 1 m above the rooftop surface in the middle of the hexahedral frame pointing towards the zenith and took images under the panels. Images were taken at one-hour intervals, between 0530hh to 1100hh at REV settings from 0 to -5 . The focal length was set to 55 mm and aperture priority mode was used with aperture of f/18. The images were acquired in both JPEG and raw formats.

To test the factory-specified gap fraction of each panel, we placed a white sheet beneath each panel on the roof surface and acquired downward-facing images under diffuse sky conditions. Diffuse sky was necessary to reduce solar radiation reflectance by the panels and to avoid underestimation of the actual gap fraction caused by panel shadows on the white sheet beneath. For each panel, nine images were taken randomly at 20 cm above the perforated panels using the DSLR (Canon EOS 600D) camera. The focal length was set to 55 mm, aperture priority mode was used with an aperture of f/5.6, and REV was set to 0 (i.e. automatic exposure was used). The images were acquired in fine quality of JPEG format. We estimated the gap fraction using Method 2 (Macfarlane, 2011). Finally, we quantified the mean and 95% confidence interval (CI) in reference gap fractions for each panel.

3. Result

3.1. Reconstruction of sky images

The mean DN in the reconstructed sky images drawn from diverse canopy structures and sky conditions agreed well (relative root mean squared error <6% and absolute bias <2.5%) with the mean of DNs in the original sky images (Fig. 3). By considering all combinations in sky conditions and canopy structures, the estimated mean of DNs in reconstructed images showed a tight linear relationship ($y = 0.98x$, $R^2 = 0.96$) with the true mean of DNs in reference sky images.

Fig. 3. Evaluation of reconstructed sky images. (a) Evaluation of the mean of DNs in reconstructed sky images against the mean of DNs in reference sky images. (b) Assembling reference sky images and canopy images. Reference sky images were collected for clear ($n = 6$), half-cloudy ($n = 6$) and cloudy ($n = 6$) conditions. Six canopy mask images were collected under forest canopies (numbers represent gap fractions). Canopy images were overlaid on the reference sky images; sky images were reconstructed; then reconstructed sky images were evaluated against the reference sky images.

3.2. Forest canopy experiment

In the closed canopy (Fig. 4), the linear conversion methods (Method 1 and 4) out-performed the binary classification method of Macfarlane et al. (2014) (Method 3). Gap fractions estimated by the binary methods were sensitive to both SZAs and REV settings (Fig. 4b and c). Gap fractions derived from Method 1 were least sensitive to SZAs. Methods 2 and 3 showed U-shaped patterns of gap fraction versus SZA, and the estimated gap fractions from Method 3 were consistently larger than those estimated by the linear conversion methods. Of the four methods, the new Method 1 estimated the smallest gap fractions and was most consistent across diverse SZAs and REV settings.

Fig. 4. Gap fraction estimates under a closed canopy on June 23, 2015 by (a) Method 1 (sub-pixel raw with scattering correction), (b) Method 2 (binary JPEG), (c) Method 3(binary raw) and (d) Method 4 (sub-pixel raw with no scattering correction). Different symbols indicate REV settings and the “Best-exposed” indicates the first unsaturated image in Method 1 (see Section 2.1.1). The subset image in (a) shows the canopy.

In the half-closed canopy, gap fractions estimated by Methods 1–3 were similar across diverse SZAs and REV settings (Fig. 5) although Method 2 (Fig. 5b) showed the most variation of gap fraction among REV settings. Gap fractions from Methods 1 and 3 were constant and similar in magnitude throughout the range of SZAs (relative coefficient of variation (RCV) <5%) regardless of REV settings (Fig. 5a and c). Correcting for scattering, which is the difference between Methods 1 and 4, substantially (up to 0.1) reduced the estimated gap fraction at low to medium SZAs (20–60°) (Fig. 5a and d). The camera position moved slightly after we acquired images at 30° of SZA, which is the cause of the lower estimated gap fractions at that SZA compared to other SZAs.

Fig. 5. Gap fraction estimates under a half-closed canopy on August 6, 2015 by (a) Method 1 (sub-pixel raw with scattering correction), (b) Method 2 (binary JPEG), (c) Method 3 (binary raw) and (d) Method 4 (sub-pixel raw with no scattering correction). Different symbols indicate REV settings and the “Best-exposed” indicates the first unsaturated image in Method 1 (see Section 2.1.1). Outliers in JPEG-derived gap fractions were removed. The subset image in (a) shows the canopy.

In the open canopy (Fig. 6), gap fractions were similar across SZAs and REV settings for Methods 1–3 but the gap fraction from Method 4 was about 0.02 larger than the other methods. In general, Method 3 was least sensitive to REV in the open canopy. Some foliage movement caused by wind made a noticeable impact on gap fraction estimates in the open canopy, as indicated by the open black boxes in Fig. 6. Method 2 showed several extremely low gap fraction estimates (e.g. lower than 0.001), which were eliminated in the figure.

Fig. 6. Gap fraction estimates under an open canopy on August 6, 2015 by (a) Method 1 (sub-pixel raw with scattering correction), (b) Method 2 (binary JPEG), (c) Method 3(binary raw) and (d) Method 4 (sub-pixel raw with no scattering correction). Different symbols indicate REV settings and the “Best-exposed” indicates the first unsaturated image in Method 1 (see Section 2.1.1). The open black boxes indicate measurements of gap fractions that are affected by wind-driven foliage movements. Outliers in JPEG-derived gap fractions were removed. The subset image in (a) shows the canopy.

3.3. Perforated panel experiment

Gap fraction of the perforated panels (Fig.7) was consistently and accurately estimated across SZAs and REV settings by Methods 1 and 3 (Fig. 7a and c). In the 0.38-gap fraction panel, JPEG-derived gap fractions agreed well with the factory-specified gap fraction, but gap fractions within the REV settings of -4 to -5 tend to estimate extreme low gap fraction values, as the open canopy experiment (not shown in the figure). Method 2 was most sensitive to REV in the panel with small gap fraction and small gap size (Fig. 7b). Method 4 showed little variation of gap fraction with REV, but consistently overestimated gap fractions at SZAs $<70^\circ$ (Fig. 7d).

Fig. 7. Evaluation of gap fraction estimates from (a) Method 1 (sub-pixel raw with scattering correction), (b) Method 2 (binary JPEG), (c) Method 3 (binary raw) and (d) Method 4 (sub-pixel raw with no scattering correction) against the factory-specified gap fractions (0.1, 0.33, and 0.38) in perforated panels. Different symbols indicate REV settings and the “Best-exposed” indicates the first unsaturated image in Method 1 (see Section 2.1.1). Outliers in JPEG-derived gap fractions were removed. Yellow shadows indicate 95% confidence interval of gap fractions in perforated panels. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4. Discussion

Our proposed new method presents four important features in image acquisition and processing to estimate gap fractions which had been addressed separately through various studies (Leblanc et al., 2005; Schwalbe et al., 2006; Lang et al., 2010; Macfarlane, 2011; Macfarlane et al., 2014). These features are (1) raw image processing to address light exposure, (2) detecting unambiguous canopy pixels to reduce effects of light scattering, (3) detecting unambiguous sky pixels to address sky heterogeneity via a reconstructed sky image, and (4) sub-pixel calculation of gap fraction in mixed pixels to improve estimation of gap fraction in small gaps (Table 1). These features enabled us to estimate gap fraction accurately regardless of solar positions, sky conditions, canopy structures and REV settings within the unsaturated image. The requirement for acquiring images under overcast sky conditions to minimize bias in gap fraction estimates has been identified as a key limiting factor in previous studies (Chen et al., 1991; Martens et al., 1993; Leblanc et al., 2005; Macfarlane et al., 2007a). Our new method provided consistent gap fractions within forest canopies regardless of SZAs and sky conditions (Figs. 3–6), the accuracy of which were confirmed through tests with perforated panels (Fig. 7). Hence, the new method allows measurement of gap fractions during the daytime, which greatly reduces the logistical challenges of indirect LAI estimation and will allow routine acquisition of more high quality data; thus contributing to better evaluation of coarse resolution LAI products from satellite remote sensing, which are key input variables in land-atmosphere interactions (Baldocchi, 1997; Ryu et al., 2011; Song et al., 2014). Assessing the image histogram for each image will necessarily slow image acquisition in the field, although modern cameras with tilt-adjustable LCD screens and live histograms mean that exposure can now be adjusted much faster than would have been possible even a few years ago,

and the additional time involved would be small. However, this also introduces some user subjectivity into the image acquisition process. If faster and more objective image acquisition is preferred (and the camera's memory storage is sufficient), images could be acquired at a range of REV (e.g. 0 to -5) without assessing the histogram in the field. Simple codes could automatically detect saturated images during image processing and analysis thus avoiding increased processing time in the lab.

	Leblanc et al., 2005	Schwalbe et al., 2006	Lang et al., 2010	Macfarlane 2011	Macfarlane et al., 2014	This study
Name			Method 4	Method 2	Method 3	Method 1
Image format	raw	JPEG	raw	JPEG	raw	raw
Raw image processing to deal with light exposure	○	△	△	○	○	○
Detecting unambiguous canopy pixels to deal with light scattering	○	○	—	○	○	○
Detecting unambiguous sky pixels to deal with sky heterogeneity via a reconstructed sky image	—	△	○	—	—	○
Sub-pixel calculation of gap fraction of mixed pixels to deal with the small gaps	○	—	○	—	—	○

Table 1. Strengths of the novel method compared to previous studies. (○: Accounted △: Partially accounted, —: Not accounted)

The new method proposes an objective and transparent REV setting scheme (Fig. 1). Although a proper REV setting is an essential factor for accurate estimation of gap fraction, the REV settings used in previous studies were inconsistent. Some studies recommended using +1 or +2 REV settings relative to the automatic exposure in the open space (Chen et al., 1991; Jonckheere et al., 2004; Zhang et al., 2005; Pekin and Macfarlane, 2009; Seidel et al., 2012). On the other hand, Macfarlane (2011) and Leblanc et al. (2005) used −1 or −2 REV settings and select the photograph which showed the largest contrast between sky and vegetation regions in blue channel histogram. However, the REV settings used in the previous

studies are depending on the canopy structures and light conditions. The REV setting scheme in Method 1 ensures that raw DNs are not saturated thus respond linearly to light intensity. This is an important benefit by raw digital image since it enables us to calculate transmittance- based gap fraction similar to the LAI-2200 plant canopy analyzer (Lang et al., 2010). To ensure a wide range of unsaturated DNs, we recommend maximum DN is located between 20 and 80% in the full range of the blue channel histogram. If REV is too low (e.g., max DN is <20% in the histogram), notable differences between vegetation and sky DNs could disappear, which could lead biased estimates in gap fraction (e.g., REV -5 in Fig. 6a) (Beckschäfer et al., 2013).

The new method successfully corrected scattering effects within canopies by forcing the unambiguous canopy pixels ($DNs < c_{andc}$, Figs. 1 and 2) to be perfectly black ($DN = 0$). The simple and straightforward scattering correction provided accurate and consistent gap fractions across diverse SZAs and REV settings in the perforated panel experiment (Fig. 7c and d). In contrast, ‘linear conversion’ without scattering correction (Method 4) overestimated gap fractions. Recently, Kobayashi et al. (2013) developed a one-dimensional, invertible, bidirectional transmission model to correct for scattering effects, which had been incorporated into the LAI-2200 instrument. Although the scattering correction model is physically robust, it requires several additional observed variables, including directional variation in sky radiation and fraction of diffuse sky radiation, and careful alignment between reference and below canopy instruments. The scattering correction scheme we propose is much simpler and more straightforward in its implementation as it requires only one raw image. Across forest canopy experiments, we found that the scattering correction effects of the gap fractions were not explained solely by SZAs (Figs. 4 a, d and 5 a, d), which question the validity of a simple scattering correction model only dependent on SZAs (Leblanc and Chen, 2001; Leblanc et al., 2005).

The new method also accounted for sky heterogeneity. Sky DNs form the baseline of incoming solar radiation, thus getting correct information on sky DNs is essential to quantify light attenuation through canopy accurately. The proposed scheme for sky reconstruction from DCP images proved reliable across diverse cloudiness and canopy structures (Fig. 3). We observed many cases where sky DNs in a DCP image varied substantially even under diffuse sky conditions, highlighting that aligning reference and canopy readings (e.g., two wands in LAI-2200 or two cameras for open and under canopies) is likely to be highly error-prone. Lang et al. (2010) proposed a scheme to reconstruct a sky image from a digital hemispherical photography, which required manual identification of pure sky pixels and needed a sky radiance model for accounting for hemisphere sky. Our process of sky reconstruction is automated and does not need a sky radiance model. Our method may need improvements or adjustments to the sky reconstruction process in some circumstances, as the tested sky conditions and vegetation structures might not work at certain cases such as leafless, white bark birch forest (Reid et al., 2014). Also, our method for detecting the point of curvature in the image histogram did not work on six of the 292 images. These were images of half-closed canopies that included strongly sunlit-leaves. Further research is desirable on the processing of images captured under poor sky conditions.

The new method most out-performed existing methods in dense canopies with small gaps. Method 3 performed at least comparably to the new method in the perforated panel experiment (Fig. 7a and c) and in open to half-closed forest canopy experiments (Figs. 5 a and 6 c). The greatest difference between the two methods was in the dense forest canopy (Fig. 4a and c). We further investigated this discrepancy in a close-up of an image from dense forest canopy (Fig. 8). It is evident that a noticeable portion of the canopy pixels in the JPEG image (Fig. 8a) were misclassified into sky pixels in Method 3 (Fig. 8b). Method 1 (Fig. 8c) agreed far more closely

with the gaps with the original JPEG image, especially where there appeared to be high foliage that might be over-exposed and slightly blurred showing through the gaps in the lower canopy. Thus, we conclude that Method 3 tends to overestimate gap fractions in very dense canopies with small gaps.

Fig. 8. (a) A subset of an original RGB image of the closed canopy (June 23, 2015, solar zenith angle at 69° , REV of -5). (b) Method 3 derived binary raw gap fraction image with REV -2 . (c) Method 1 derived gap fraction image. Grey bar indicates gap fractions in (c)

Gap fractions from JPEG images (Method 2) agreed well with the new method in non-dense forest canopies (Figs. 5 and 6) but Method 2 performed poorly in dense, closed canopies. Good performance of the Method 2 in sparse canopies was consistent from previous studies (Ryu et al., 2012; Macfarlane et al., 2014). Under the dense forest canopy (Fig. 4), JPEG-derived gap fractions varied substantially with REV setting. The perforated panel experiment also confirmed that JPEG-derived gap fractions were overall within the uncertainty ranges of gap fractions for the 0.38 and 0.33 gap fraction panels (Fig. 7b) but JPEG images from the 0.10 gap fraction panel with small gaps once again resulted in large variation of estimated gap fraction across REV settings. Thus, the proper choice of REV setting remains critical for estimating gap fraction using JPEG images, especially in dense canopies. Concurrent recording of both raw and JPEG images revealed the optimal REV for JPEG images. In the dense forest canopy, JPEG-derived gap fractions were closer to the Method 1 derived gap fractions at REV settings of -4 and -5 (Fig. 4b), which was the REV range where pixel DNs from raw images were not saturated. All raw images at REV settings >-4 included saturated pixels in the dense forest canopy experiment. Only a few studies recommended using REV settings of -4 or -5 under dense canopy (Chen et al., 1991; Macfarlane et al., 2000). Similarly, gap fractions estimated from JPEG images were closest to the true value of the gap fraction of the 0.1 panel at REV settings of -3 to -5 (Fig. 7), which was once again the range of REV for which raw images contained no saturated pixels. Thus, we recommend using the JPEG images which are converted from the unsaturated raw images (Fig. 1a). As inexpensive digital cameras such as the Raspberry Pi micro-camera allow raw image acquisition, the use of raw image for measuring gap fractions will become easier and popular.

The new method is fully automated and modular such that any part of the process can be improved if necessary (Fig. 1). The use of raw images

is a pronounced strength over JPEG-derived image acquisition and processing methods, in which the data are modified knowingly or unknowingly by users during image processing. For example, Macfarlane et al. (2014) applied different gamma corrections to raw images, but could not achieve a similar blue channel histogram in JPEG images. Camera manufacturers do not reveal all the algorithms applied to raw data prior to producing the final JPEG image, which impeded advancements in image acquisition and analysis (Frazer et al., 2001; Inoue et al., 2004; Lang et al., 2010). In this study we applied the method to broadleaf canopies only, and further evaluation of the novel method for needle-leaf trees will be needed.

5. Summary and conclusion

We report a novel protocol for image acquisition and processing to measure gap fractions accurately under various sky conditions and canopy structures. Our protocol suggests:

- Reduce the REV by adjusting the f -number in aperture priority mode to acquire an unsaturated raw image
- Extract the blue channel raw image with dark current correction to obtain DNs that are linearly related to light intensity
- Identify the unambiguous sky (skyuc) and vegetation (candc) Regions by analyzing the blue channel histogram
- Interpolate the unambiguous sky and cloudy pixel (DNs > skyuc) to reconstruct the sky image
- Force the unambiguous canopy pixels (DNs < candc) to be perfectly black (DN = 0) to correct the scattering effect by leaves
- Compute gap fraction as the ratio of mean in DNs of the scattering corrected canopy image and the mean in DNs of the reconstructed sky image

We demonstrated that our protocol delivered reliable performance across diverse canopy structures and sky conditions, including the daytime. We expect the novel protocol will contribute to expanding the field observation time and better evaluating coarse satellite-based LAI products.

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Abstract (Korean)

디지털 카메라 사진 (DCP)은 수목 gap fraction을 간접적으로 측정할 수 있는 방법으로 떠오르고 있다. 하지만 사진을 활용한 gap fraction 추정은 상당한 불확실성을 야기하는데, 그 이유는 픽셀 분류 시 카메라의 상대 노출 값 (REV)과 임계 값을 설정하기 때문이다. 본 연구에서는 다양한 태양고도 (SZAs), 하늘 상태, 그리고 수목 밀도 아래에서도 gap fraction 추정을 향상시킬 수 있는 새로운 방법을 제시한다. 이 방법은 DCP에서 얻은 불포화 raw 이미지를 통해 하늘을 재구성하고, 식생 혹은 하늘 픽셀인지 모호한 픽셀들까지 gap fraction 추정 시 사용함으로써 raw 이미지의 이점을 최대한 활용하였다. 또한, 수목 내에 존재 할 빛 산란 효과를 미리 명백한 식생 또는 하늘의 픽셀로 분류하는 방법과 결합하여 그 효과를 크게 감소 시켰다. 새로운 방법의 민감성을 확인하기 위해, 우리는 태양고도가 20°에서 85° 일 때 1시간 간격으로 REV를 0에서 -5로 설정하여 폐쇄된, 반 폐쇄된, 그리고 개방된 수목 아래에서 사진을 습득하였다. 폐쇄된, 반 폐쇄된, 그리고 개방된 수목 아래에서 추정 한 gap fraction은 다양한 태양고도에도 불구하고 작은 변화를 보여주었다. Gap fraction의 정확도를 실험하기 위해 사용 된 천공 패널 실험은, 구멍 크기, 간격, 그리고 SZAs의 범위에 걸쳐도 정확하게 gap fraction을 추정 할 수 있다는 것을 확인 할 수 있었다. 우리는 본 연구에서 제시한 새로운 방법이 태양고도와 개방된 수목부터 폐쇄된 수목에 상관없이 gap fraction을 정확하게 추정할 수 있는 기회를 마련하며, 수관과 엽면적지수 (LAI)의 정확하고 정밀한 모니터링에 상당한 전진을 보여주고, 위성 원격 탐사의 LAI 산물을 교정 및 평가하는데 활용될 것이라고 결론지었다.

주요어 : 엽면적지수, gap fraction, 디지털 카메라 이미지, 빛 노출, 원격 탐사

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