USE OF AIRBORNE LASER SCANNING DATA FOR THE ASSESSMENT OF TREE CONDITION

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ABSTRACT: The condition of trees is an important indicator to manage the forested area. To survey trees by remote sensing, previous works often used the vegetation indices which were based on spectral characteristics observed from optical sensors. This study attempted to use airborne laser scanning (ALS) data for the assessment of tree condition, and evaluate the performance of ALS methods by comparing with the exiting optical indices. Fifty-six broad-leaved deciduous trees (*Cerasus* species) were selected for this study. As the study area, the individual crown of trees was identified in the field. And we measured the condition of each tree by following ground indicators ; growth of crown (Gc), growth of shoots, individual tree volume (Vol), plant area index (PAI), woody area index (WAI), leaf area index (LAI), leaf chlorophyll content and leaf water content. The small footprint ALS and 4-band (blue, green, red, and near infrared) digital camera dataset was simultaneously acquired on August in 2010, from the helicopter at 300m altitude. At the scale of individual crown, we derived the ALS estimators including the sum of plant area density (∑PAD), vegetation fraction (VF), and also calculated the leading optical indices, e.g., NDVI, Green NDVI. As the result of correlation analysis, the ALS indices showed better performance than the tested optical indices in estimating Gc (r=0.698 with VF), Vol (r=0.818 with ∑PAD), PAI (r=0.688 with ∑PAD), WAI (r=0.789 with ∑PAD), and LAI (r=0.636 with ∑PAD). That was because 1) ∑PAD could measure the three-dimensional amount of plant materials, which would be abundant for the trees under good condition but sparse under poor condition, and 2) VF, indicating the ground cover by trees, would be related with the capture of sunlight energy. These aspects of tree condition are important and better explained by ALS indices than optical indices.

1. INTRODUCTION

The condition of trees is an important indicator to manage the forested area, because trees are the fundamental component of the landscape. To survey tree condition at a broad scale, remote sensing (RS) is expected to be more efficient than field practices. On-going advances in RS dataset provide high-spatial resolution imagery enough to observe canopy at the single-tree level. Especially in the observation from airborne platform, the condition of individual tree crown is detectable from the sensor, with tens to hundreds of records.

Vegetation index (VI) can be simply applied to the assessment of tree condition. VIs are calculated from the spectral data of targets, which is observed from an optical sensor. The leading VIs (e.g., NDVI, SR) (Rouse et al. 1974; Jordan 1969) are based on the principle that typical vegetation spectra absorb relatively more red light than near-infrared light. Green spectral region is also significant to develop the sensitivity to chlorophyll content, as included in the calculation of Green-NDVI or Red Green Index (Gitelson and Merzlyak 1997; Song et al. 2011a). However, the spectral values used in these VIs are likely to be affected by the geometry among the sun, canopy and sensor (Gu and Gillespie, 1998; Soenen et al. 2005), or the shadowing effect from adjacent trees (Li and Strahler, 1992; Kane et al., 2008). These influences on a tree spectrum are problematic when using the VIs for the assessment of tree condition.

Moreover, diagnosis based on the spectral features of trees seems to be limited in the assessment of leafy part. As shown in Figure 1, tree condition can be described not only by the photosynthetic tissues but also the non-photosynthetic parts of trees, e.g., the state of shoots, branches or stems. To enlarge the extent of RS assessment for tree condition, the other type of RS-sensor (e.g., laser scanner) dataset should be studied.

Airborne laser scanning (ALS) data is able to describe the 3-dimensional figure of trees by recording the position of laser pulses, which are reflected from the target. In previous studies, the numbers of laser-pulses were related with gap fraction (Morsdorf et al., 2006; Sasaki et al., 2008), or contact frequency (Hosoi and Omasa, 2006, 2009; Hosoi et al. 2010). These factors were used in the estimation of leaf area density (LAD, the total area of leaves per unit volume), leaf area index (LAI, the total area of leaves per unit ground area), or stand volume (Ioki et al., 2009) for the unit plot. However, in terms of tree condition assessment at the single-tree level, the use of ALS data has yet to be studied.

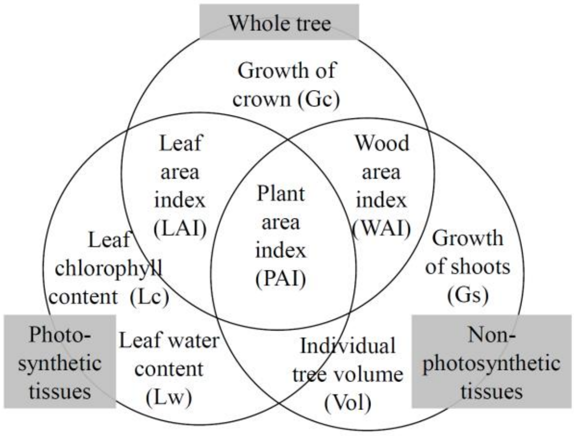

Figure 1 Tree condition indicators surveyed on ground

In this study, tree condition is used as a comprehensive term to diagnose trees, including the state of photosynthetic and non-photosynthetic parts at the moment (Figure 1). Also, it takes into account the growth of crowns or shoots for a given period. The tree condition, accordingly, cannot be measured directly by a single indicator (Ferretti, 1997; Dobbertin 2005). Thus, RS methods should be developed based on more than single *in-situ* indicators.

The objective of this study is to assess tree condition using small-footprint and high-density ALS dataset. Specifically, (1) we attempt to develop the ALS-derived indices effective in the assessment of tree condition. And (2) the potential of ALS indices is evaluated by comparing with the performance of optical vegetation indices obtained from airborne spectral imagery.

2. MATERIALS AND METHODS

2.1 Plant materials

Fifty-six cherry trees (*Cerasus* × *yedoensis* 'Somei-yoshino') in the Expo'70 Commemorative Park, Osaka, Japan, were selected for the ground materials. The trees were planted on the side of pedestrian way of the park for 30 to 40 years ago, as the saplings in a similar size. But now the conditions of these trees show a variety of states.

We identified the crown boundary of each tree on field, and carefully drew the individual crown polygons not to be overlapped with each other, referring to the false-color airborne digital camera image (Section 2.2). All the analyses of remote sensing data are based on the 56 crown-polygons.

2.2 Airborne remote sensing dataset

The ALS data were collected on 24 August 2010, under cloud-free conditions, from 300m flying height, and by the Riegl LMS-Q560 mounted on a helicopter. The specifications were set to 1550nm wavelength of laser pulse, maximum ±30° scan angle, multiple-pulse mode, and a footprint with a diameter of 15 cm (0.5-mrad). Across all the study area, the average density of laser-returns was 51.8 returns/m^2. This dataset was used for calculating ALS indices (Section 2.3).

Simultaneously with the ALS observation, we collected airborne digital camera image of 4 spectral bands (blue, green, red and near-infrared), with FWHM-range of approximately 60~100nm and 0.2-m spatial resolution. The image was orthorectified with the ALS data. Using this spectral information, we calculated the optical VIs (Section 2.4).

As the ancillary data, we used another ALS dataset; it was acquired on 4 October 2004, from 1000m flying altitude by Airborne Laser Terrain Mapper 2050 (Optech Inc.), with 38cm diameter footprint and 11.3 returns/m^2 point-cloud density. This dataset was only used to obtain tree height in 2004, for measuring the growth of crown (Table 1).

2.3 ALS indices

We tested following 5 ALS indices; ∑PAD, PAI_{RS}, VF, OGF and GF.

Plant area density (PAD), defined as the total area of plant materials (e.g., leaves, branches, stem) per unit volume, is the principal unit to describe the three-dimensional composition of canopy structure (Takeda et al., 2008; Hosoi and Omasa, 2009; Hosoi et al., 2010). The vertical integration of PAD is given as plant area index (PAI, the area of plant materials per unit ground area). These PAD and PAI are used instead of LAD and LAI, when it is difficult to separate leaves from other non-photosynthetic tissues (e.g., branches, stems). Using ALS dataset, the PAD can be estimated at a voxel level, as follows (Hosoi and Omasa, 2009; Song et al. 2011b);

$$\mathrm{PAD_{ijk}} = \frac{1}{K} \cdot \frac{1}{\Delta h} \cdot \frac{N_I(V_{ijk})}{N_I(V_{ijk}) + N_P(V_{ijk})} \qquad (1)$$

where $N_I(V_{ijk})$ and $N_P(V_{ijk})$ are the numbers of intercepted and passed laser-pulses at a voxel V_{ijk}, respectively. The parameter K, the laser beam attenuation factor, is given as constant equal to 0.9 in previous studies (Weiss et al., 2004; Hosoi and Omasa, 2006, 2009). The voxel size in this study is set to 1m, thereby the layer thickness Δh is given as 1. We summed the PADs ($\sum$PAD) of all voxels distributed in the tree crown area, for indicating the amount of plant materials of the tree. If trees are of the similar age and developing state (Section 2.1), the amount of plant materials can be an indicator to present the condition. Therefore, the high $\sum$PAD may describe a tree at the good vigor stage which has a large amount of foliage, branches and shoots in the three-dimensional space.
And the PAI at a level H in the tree canopy is related to PAD (h) at level h in the canopy through

$$\mathrm{PAI} = \int_0^H \mathrm{PAD(h)} \cdot \mathrm{dh} \qquad (2)$$

To distinguish from ground-measured PAI, the ALS-estimated PAI is herein referred to as the PAI_{RS}. We used the mean PAI_{RS} value obtained from each tree crown area (Section 2.1), as the estimator.
Vegetation fraction (VF; Morsdorf et al., 2006; Sasaki et al., 2008) is calculated as follows;

$$\mathrm{VF} = \frac{N_{vg}}{N_{all}} \qquad (3)$$

where N_{vg} is the number of laser-echoes which are returned from vegetation (i.e., trees in this study) and N_{all} is the number of all the incident pulses. Accordingly, good-condition trees having denser crowns than poor-condition trees, may show higher VF because more laser pulses are intercepted by trees.
Sasaki et al.(2008) applied the type of laser-echoes (i.e., First, Last, and Only) to this VF calculation.

$$\text{"Only" and Ground Fraction (OGF)} = \frac{N_{op\cap gr}}{N_{op}} \qquad (4)$$

$$\text{Ground Fraction (GF)} = \frac{N_{gr}}{N_{op} + N_{fp}} \qquad (5)$$

where N_{op} is the number of ‘‘Only” laser-echoes, $N_{op\cap gr}$ is the number of ‘‘Only” laser-echoes returned from the ground, N_{gr} is the number of laser-echoes on the ground, and N_{fp} is the number of “First” laser-echoes. The OGF and GF were effective to estimate LAI and canopy openness (Sasaki et al., 2008).
We tested these VF, OGF and GF as the indicators of ground cover by trees, which can be considered as the proportion of sunlit area covered with plant materials. The values of indices were averaged in each tree crown polygon (Section 2.1).

2.4 Optical indices

We calculated the 3 leading optical indices; NDVI, normalized difference computation of the reflectance in the near-infrared and red bands, Green NDVI (G-NDVI), normalized difference between the near-infrared and green reflectance, and Red Green Index (RGI), a ratio of red to green reflectance. The mean index-value obtained from each tree crown area (Section 2.1) was used as the optical-VIs estimator for the tree condition.

Table 1. On-ground tree condition indicators

Indicator	Abbreviation	Description	Unit	Data source & Measurement	Reference
Growth of crown	Gc	vertical growth per unit ground area for a given period	cm/m^2	crown height from ALS dataset in 2004, 2010	Yu et al, 2004
Growth of shoots	Gs	mean elongation of shoots for recent 9 years	cm/year	mean length between the bud scale scars of sampled shoots	Takahashi and Yoshida, 2009
Individual tree volume	Vol	stand volume at the single-tree level	m^3	field-measured DBH, ALS-derived tree height	Ioki et al, 2009
Plant area index	PAI	the area of plant per unit ground area	m^2/m^2	hemispheric photo taken in the leaf-on season	Weiss et al, 2004
Wood area index	WAI	the area of woody parts per unit ground area	m^2/m^2	hemispheric photo taken in the leaf-off season	Bréda, 2003
Leaf area index	LAI	the area of leaves per unit ground area	m^2/m^2	the difference between PAI and WAI	Bréda, 2003
Leaf chlorophyll content	Lc	the content of chlorophyll a and b	$\mu g/cm^2$	leaf spectra measured from the sampled leaves	Imanishi et al, 2010
Leaf water content	Lw	the ratio between the quantity of water and the area	g/cm^2	field weight, oven-dry weight, leaf area of the sampled leaves	Ceccato et al, 2001

2.5. Ground indicators

To assess the performance of RS indices, *in-situ* tree condition was measured by following 8 indicators; growth of crown(Gc), growth of shoots(Gs), individual tree volume(Vol), plant area index(PAI), wood area index(WAI), leaf area index(LAI), leaf chlorophyll content(Lc) and leaf water content(Lw). The definitions and measurement methods are summarized in Table 1.

2.6. Correlation analysis and PCA (principle component analysis)

The correlation between RS indices and ground indicators was assessed with Pearson's *r*. And then the number of ground indicators was reduced by PCA. This data reduction could contribute to understand tree condition from a holistic viewpoint. To explain the extracted components by using RS indices, we built the regression models. This series of analyses could clarify the performance of RS indices in the assessment of tree condition.

3. RESULTS AND DISCUSSION

3.1. The relationship between RS indices and *in-situ* tree condition indicators

Table 2 showed the result of correlation analysis.

Gc is the most correlated with VF (r=0.698), and followed by PAI_{RS} (r=0.675). Remind that VF can be considered to indicate the proportion of sunlit area covered with plant materials (Section 2.3). Therefore, the more tree covers (i.e., larger VF) result in more possibility to use sunlight energy, and then the tree shows more growth (i.e. larger Gc). This trend is also shown in the other ALS indices, OGF and GF. The relationships are strong but negative, as -0.649 in OGF and -0.655 in GF respectively, because they are designed to present the canopy openness (Section 2.3).

The strong correlations with Gs are found for G-NDVI (r = 0.634) and NDVI (r = 0.633). Gs can be regarded as the performance of transporting nutrients from root tissues and the availability of nutrients for leaves at the shoots. This kind of shoots elongation forms a dense and large amount of foliage (r = 0.579 in ∑PAD) in good condition, thereby showing the strong chlorophyll absorption in the spectrum (i.e., larger G-NDVI and NDVI).

The correlation between Vol and ∑PAD is remarkable (r=0.818), indicating that the trees of larger DBH and higher tree height (i.e. larger volume) have a large amount of plant materials (i.e. larger ∑PAD). This trend is also shown in the other ground indicators; ∑PAD was also the best index in PAI(r = 0.688), WAI(r = 0.789) and LAI(r = 0.636). The PAI, WAI or LAI is often used to indicate the composition of canopy structure (Bréda, 2003; Weiss et al., 2004), thereby closely related with ∑PAD (Section 2.3).

The correlation of Lc with RS indices is significant but moderate ($|r|$ < 0.55 in all tested indices). That is because the spectral figures at a leaf scale are different from those at canopy scale (Zarco-Tejada et al., 2001). The canopy spectra used to be affected by shadowing effects by adjacent trees or branches, leaf inclination, the distribution of photosynthetic and non-photosynthetic tissues, and so on (Li and Strahler, 1992; Jacquemoud, 1993; Kane et al., 2008). These effects may cause the difference between Lc and the RS indices. Our spectral measurement does not include the wavelengths of the water absorption. However, Lw is well-correlated with NDVI (r=0.773), G-NDVI (r=0.773), and ∑PAD (r=0.756). This result can be explained as follows; the trees under water stress (i.e., lower Lw)

Table 2. Pearson's *r* between ground indicators and RS indices used in the tree condition assessment (N=56)
The highest, second and third correlations in each ground indicator are shown as bold character in a dark-gray cell, bold in a light-gray cell, and bold in a white cell, respectively. All correlations are significant in p<0.01, except for gray characters (p>0.05).

		On-ground tree condition indicators							
		Gc	Gs	Vol	PAI	WAI	LAI	Lc	Lw
ALS-derived index	∑PAD	0.356	**0.579**	**0.818**	**0.688**	**0.789**	**0.636**	**0.542**	**0.756**
	PAI_{RS}	**0.675**	0.486	**0.675**	0.467	0.516	0.437	0.424	0.555
	VF	**0.698**	0.473	0.639	0.450	0.503	0.420	0.437	0.557
	GF	**-0.655**	-0.541	-0.626	-0.464	-0.510	-0.435	-0.522	-0.586
	OGF	-0.649	-0.478	-0.600	-0.539	-0.558	-0.515	-0.419	-0.591
Optical vegetation index	NDVI	0.535	**0.633**	**0.677**	**0.629**	**0.704**	**0.586**	**0.529**	**0.773**
	Green-NDVI	0.508	**0.634**	0.669	**0.629**	**0.707**	**0.586**	**0.540**	**0.773**
	RGI	0.478	0.199	0.308	0.201	0.198	0.195	0.058	0.248

may tend to decrease the loss of water vapor transpired at the leaves, by lessening the foliage body (i.e., lower NDVI or G-NDVI). The lessened foliage body can be described by the index of three-dimensional amount of plant materials (∑PAD), rather than the index of the two-dimensional canopy cover ($|r| < 0.6$ for PAI_{RS}, VF, GF and OGF).

3.2. Important ground-factors to assess tree condition

As the result of PCA, the 8 ground indicators could be reduced as two components (PC1, PC2). The components were extracted by varimax rotation converged in 3 iterations, with eigenvalues greater than 1. PC1 and PC2 accounted for 76.5% of the total variance.

The ground indicators were remarkably grouped into PC1 and PC2, except for Lw (Table 3). PAI, WAI, LAI and Vol were found to load on the PC1, which could be labelled “the amount of canopy elements”. Gc, Gs and Lc also loaded on the PC2, which could be labelled “tree vitality”. Lw could be incorporated into both of PC1 and PC2.

3.3. The potential of LS indices

The two components, the amount of canopy elements (PC1) and tree vitality (PC2), were estimated by the regressions of RS indices. The models were built by stepwise method to employ only the effective RS indices for the components. RS indices that showed strong correlations with ground indicators (∑PAD, PAI_{RS}, VF, NDVI and G-NDVI) were tested as a variable in the regression models with the criteria of F-probability to enter ≤ 0.05 and to remove ≥ 0.1.

As a result, the amount of canopy elements (PC1) was explained by the regression of ∑PAD (adjusted R^2=0.429) ; this result is understandable because the ∑PAD is a RS index for presenting the 3-dimensional occupation of plant materials.

And tree vitality (PC2) was explained by the model employing VF and G-NDVI (adjusted R^2=0.479) ; this result may be based on that the growth of shoots or crown is promoted by the interception of sunlight energy (VF) and the performance of chlorophyll contents (G-NDVI).

Table 3. The results of PCA (the left-side block) and stepwise regression models (the right-side block)

	Rotated Component Matrix	
	PC1	PC2
PAI	0.960	0.149
LAI	0.937	0.089
WAI	0.911	0.331
Vol	0.633	0.508
Lw	0.602	0.598
Gs	0.284	0.822
Gc	-0.026	0.777
Lc	0.329	0.712

Factors from PCA	Label	Selected variable(s)	Adjusted R^2	Model*
PC1	The amount of canopy	∑PAD	0.429	$-0.878 + 0.005 \cdot \sum PAD$
PC2	Tree vitality	VF, G-NDVI	0.479	$-6.131 + 6.778 \cdot VF + 7.519 \cdot G\text{-}NDVI$

* Models and the coefficients are significant in $p<0.01$

4. CONCLUSION

The remotely sensed indices derived from ALS dataset were useful in the estimation of on-ground indicators for tree condition. Among the tested ALS indices, the sum of plant area density (∑PAD), indicating the three-dimensional occupation of plant materials, showed potential to estimate *in-situ* individual tree volume, PAI, WAI and LAI, rather than other tested optical vegetation indices. Those indicators can be categorized into “the amount of canopy elements” of trees. And vegetation fraction (VF), an ALS index to describe the proportion of sunlit area in the tree crowns, can be used with the optical index Green NDVI for estimating “tree vitality”, i.e., the growth of crowns or shoots and leaf chlorophyll contents. This performance of ALS indices will contribute to the comprehensive assessment of tree condition.

In future studies, these potentials of ALS indices should be more validated in terms of the specification of the used ALS dataset, e.g., dependency to the type of echoes, the density of laser pulses, or the size of footprint.

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