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Technical Note

Linking remote sensing techniques and leaf area index

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Summary: Leaf area index (LAI) is a key forest canopy variable with close links to forest growth, health, and productivity. For forest managers knowledge of LAI offers the potential to identify site limitations and monitor forest response to targeted interventions such as fertilisation. Until recently vegetation indices (VIs) derived from multispectral imagery offered the only means of estimating LAI over large areas. These techniques are not well suited to coniferous forests where high LAI causes sensor saturation.

Light Detection and Ranging (LiDAR) offers a new approach for estimating LAI in forest ecosystems. A variety of approaches have been successfully demonstrated but few have been trialled in New Zealand's managed plantation forests.

This technical note presents results from a study examining the correlation between ground measurements of LAI, vegetation indices derived from satellite imagery, and LiDAR metrics. LAI measurements were obtained from 20 plots located in *Pinus radiata* D. Don plantations in the central North Island, New Zealand. A variety of LiDAR metrics and vegetation indices were calculated for each plot. The correlations between measured LAI and the calculated variables were determined for each plot.

The only VIs significantly correlated with LAI were the simple ratio ($r(18)=0.48$, $P<0.05$), and the normalised difference vegetation index ($r(18)=0.46$, $P<0.05$). There was evidence of sensor saturation in both indices, restricting their applicability to very young stands with LAI less than 2. None of the ratios utilising the novel red-edge spectral band were significantly correlated with LAI.

All but one of the LiDAR metrics were significantly correlated with LAI. The percentage of first returns above mean return height had the highest correlation coefficient ($r(18)=0.85$, $P<0.001$). Metrics which were strongly correlated with LAI in other studies did not perform well in our study, confirming that LiDAR-LAI relationships remain site and campaign specific.

The LiDAR-LAI correlation coefficients in our study are some of the highest observed in this forest type. Future work will attempt to utilise the correlations between ground based LAI and remotely sensed variables to develop predictive models for LAI.

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Introduction

Leaf area index (LAI) is a measure of leaf surface area per unit ground area and is closely linked to forest growth, health, and productivity[1]. LAI is strongly influenced by site fertility, water availability, and stand conditions[2]. Site interventions such as fertilisation, irrigation, site preparation, and silvicultural operations can produce large changes in LAI[1]. Fertilisation in particular can produce rapid and large changes in stand LAI with associated gains in stem increment[2,3].

For forest managers, LAI offers the potential to identify areas with low productivity and monitor the response to appropriate interventions[3,4]. In addition, LAI is valuable for use in emerging physiological and hybrid growth models which seek to incorporate potential light use into growth forecasts.

Despite the fundamental importance of LAI to forest managers and scientists, usage has been limited by the difficulty of obtaining accurate and cost-effective LAI measurements. Direct assessment in coniferous forests requires destructive sampling of selected trees within a stand. Indirect assessment using optical techniques can rapidly measure effective LAI, which includes non-photosynthetic plant elements. These techniques offer a more practical option, and have been widely used in the research community[5]. However, measurement using indirect optical methods are restricted to sunrise, sunset, and on overcast days with no discernible difference in cloud layer brightness. These requirements place serious logistical constraints on the number of samples that can be obtained[6].

Remote sensing techniques linking spectral properties of vegetation with ground measurements have been used to estimate LAI over large areas for several decades. However, the vegetation indices (VIs) used in remote sensing techniques suffer from band saturation in areas with high LAI values such as conifer plantations[1,3]. Rapid advances in sensor technology have led to the development of new VIs targeting LAI and photosynthetic activity.

Approximately one third of surveyed commercial forestry companies in New Zealand already purchased imagery capable of delivering some of these VIs; however bands outside of the visible wavelengths were not widely utilised[7]. Furthermore, multispectral imagery (albeit at coarser resolutions of 30 m) from platforms such as Landsat 8 can be obtained for no fee. As such, there is the potential that VIs available from existing data streams could produce acceptable LAI estimates in certain settings with little extra cost. To date, assessments of the strength of association between many of the candidate VIs and LAI have largely been restricted to crop canopies[8].

LiDAR offers a novel approach for estimation of LAI over large areas. An emerging body of research has shown that LiDAR metrics can accurately predict LAI in coniferous forests. LiDAR-LAI estimates have also been shown to be less sensitive to saturation at high LAI levels[9,10].

To date, very limited research on LiDAR-LAI estimation has been conducted in New Zealand's plantation forests. Results from early work done in this area demonstrated that simple LiDAR metrics provided accurate estimates of LAI (R^2=0.8) for stands of *Pinus radiata* D. Don[11]. While useful as a proof of concept, this research relied on destructive measurement of LAI for model development, and hence was limited to a small area comprising a single age class.

A large number of LiDAR metrics have been proposed for estimating LAI, with varying degrees of complexity and success[12]. Some of the best results have been achieved using a new class of canopy penetration metrics developed to target LAI estimation; however these are often constrained to a specific LiDAR campaign and forest type[3,12]. In general, it is accepted that the choice of height threshold (the elevation below which all returns are classified as ground returns) and plot radius have a large impact on model selection and performance[6,12]. This poses a challenge for larger LiDAR surveys, where altering plot radius and height threshold may require significant additional data processing.

Research is currently being undertaken to investigate the feasibility of using satellite and LiDAR data for large scale estimation of LAI within New Zealand's plantation forests. This technical report presents results from a pilot study using ground based measurements of effective LAI from 20 plots to identify correlations between LAI and LiDAR metrics. These correlations are compared to those obtained between LAI and a range of vegetation indices, including new vegetation indices utilising novel spectral bands.

Methods

Plot selection

The data used were acquired from Kaingaroa forest which is located in the Central North Island of New Zealand (38.67S; 176.46E). For the pilot study, LAI was measured in 20 plots drawn from the network of plots established in the estate for use with remotely sensed data. Plot locations were determined using a systematic sampling approach where the nodes of a grid with random origin and orientation form plot centres. The instrumentation chosen for ground measurement of LAI required continuous observation of sky brightness from an open clearing close to each plot. Suitable clearings were identified using satellite imagery and adjacent plots were selected at random to form the study dataset.

Each circular plot bounded 600 m^2, and the chosen plots covered a wide range of stand densities (200 – 917 stems ha^{-1}). Estimates of stand height ranged from 17 m to 39 m (mean of 18 m), while stand ages ranged from 10 to 26 (mean and median of 18). The maximum gradient of plots was 14%, but most were on relatively flat terrain.

LAI measurements

LAI measurements were acquired in late August 2014 using the LAI-2200C Plant Canopy Analyser (LI-COR Biosciences Inc., Lincoln, NE, USA). This is a new optical instrument that allows LAI measurements to be obtained under clear skies, greatly increasing the number of suitable days for sampling. Clear sky measurement is achieved by removing the effects of scattered radiation originating from clear blue sky on estimates of canopy gap fraction used to calculate LAI[13]. Plot mean LAI was calculated from 18 measurements taken within each plot. Measurements were obtained on cloud free days using the recommended protocol[13]. Corrections for scattered light required knowledge of needle optical properties and solar position. Needle spectra were obtained from fresh needle samples measured using a spectroradiometer. Solar position was calculated from GPS time and location recorded during plot measurements. The outer sensor ring of the LAI-2200C was excluded from all LAI calculations. This ‘mask’ restricts the instrument’s view zenith angle to between 0-58°. This zenith range has been observed to produce stronger correlations with remotely sensed data, which is usually collected with small offsets from nadir[6].

LiDAR data

Aerial LiDAR data were collected in early 2014 using an Optech Pegasus scanner. Calculation of LiDAR metrics was completed using the FUSION software package[14]. Penetration metrics successfully used in LiDAR-LAI estimation were identified from the literature and classified according to type. Metrics derived using variable height thresholds, altered plot radii, or pulse intensities were excluded. These metrics have been identified as poor candidates for generalised LiDAR-LAI models as they are often campaign specific, require repeated processing, and lack theoretical justification[3,6,12]. A subset of height related metrics which have been useful in other studies were also included in the analysis. Table 1 shows the full list of LiDAR metrics selected for evaluation.

Table 1. LiDAR metrics calculated for all plots. ‘In canopy’ hits were defined as all returns above 2.5 m.

Metric acronym	Description	Source
PFAM	Percentage first returns above mean return height	FUSION canopy metrics
ELK	Elevation L-moment kurtosis	FUSION descriptive metrics
ECV	Elevation coefficient of variation	FUSION descriptive metrics
FG_AG	First ground / all ground returns	Summary data
SGR	Single ground returns	Summary data
P30	30^{th} height percentile from all canopy returns	Beets et al.[11]
GT	Ground / all returns	Zhao & Popescu[12]
RIGT	In canopy + ground / all returns	Zhao & Popescu[12]
LPM	-2.56ln (In canopy + ground / all returns)	Zhao & Popescu[12]
LPI	Ground / ground + all returns	Peduzzi et al.[3]

Table 2. Vegetation indices calculated from 5 m resolution RapidEye satellite imagery. Modified from Kross et al.[8]

VI Acronym	Vegetation index	Equation
NDVI	Normalised difference vegetation index	$(R_{NIR} - R_{RED}) / (R_{NIR} + R_{RED})$
SR	Simple ratio	R_{NIR} / R_{RED}
GR	Near-red green ratio	R_{NIR} / R_{GREEN}
VI	Green red ratio	R_{GREEN} / R_{RED}
gNDVI	Green NDVI	$(R_{NIR} - R_{GREEN}) / (R_{NIR} + R_{GREEN})$
NDVIre	Red edge normalised difference vegetation index	$(R_{NIR} - R_{RED\text{-}EDGE}) / (R_{NIR} + R_{RED\text{-}EDGE})$
SRre	Red edge simple ratio	$R_{NIR} / R_{RED\text{-}EDGE}$
MTVI2	Modified triangular vegetation index	$1.5[1.2(R_{NIR} - R_{GREEN}) - 2.5(R_{RED} - R_{GREEN})] / \sqrt{[(2R_{NIR} + 1)2 - (6R_{NIR} - 5\sqrt{(R_{RED})}) - 0.5]}$
RTVI	Red edge triangular vegetation index	$100(R_{NIR} - R_{RED\text{-}EDGE}) - 10(R_{NIR} - R_{GREEN})$

Satellite imagery

Satellite imagery was acquired using the RapidEye satellite constellation during January 2014. The RapidEye constellation has a resolution of 5 m and is notable for collecting red-edge (690-730 nm) spectral data[15]. This portion of the spectrum is useful for assessing vegetation health and stress, and has been used to derive novel vegetation indices with close links to LAI[8]. A survey of the relevant literature was conducted to identify candidate vegetation indices. Table 2 shows the full list of vegetation indices chosen for analysis.

Data analysis

The satellite and LiDAR data were used to calculate the vegetation indices and LiDAR metrics for each plot.

The Pearson's product moment correlation coefficient (r) was calculated between vegetation indices and measured LAI. All correlations with measured LAI were tested for significance (α=0.05). The process was repeated for LiDAR metrics and measured LAI.

Published results from other studies examining the relationship between LIDAR / VI metrics and LAI included both correlation coefficients (r) and coefficients of determination (R^2). In the case of simple linear regression the two are mathematically related. However, r indicates both the magnitude and direction of the relationship, and comparison between r and R^2 is not applicable where the coefficient of determination is obtained from multiple regression. Both are useful for evaluating the association between variables, and wherever we reported on other studies we included the coefficients as reported in the original work.

All calculations and statistical analyses were performed using R statistical software[16].

Results and discussion

Vegetation indices

VIs were weakly correlated with LAI (Table 3), with only NDVI and SR producing significant correlations with measured LAI (P<0.05). Both ratios exploit the high fraction of visible red light absorbance in healthy foliage. NDVI in particular has been widely used to estimate LAI; however the strength of the relationship is sensitive to forest type, canopy closure, image quality, and background vegetation[17]. Higher correlations than those we obtained have been observed in pine forests, but only within stands of a single age class and even canopy closure[18]. The LAI range of the study plots (2-6) can cause saturation of the spectral bands and we identify this as the most likely cause of the weak correlation between NDVI and SR with LAI in our study[1,3].

The marked change in light absorbance across the red to near infrared (red-edge) spectral region is closely linked with chlorophyll content, and VIs utilising the red-edge have the potential to improve estimation of LAI[8]. However, in a study estimating the LAI of crop canopies from satellite imagery, Kross et al.[8] found that NDVIre, SRre, and RTVI were no better than NDVI at predicting LAI. Our results suggest that NDVI (and the closely related SR) are also more highly correlated to LAI in forest canopies than the red-edge VIs. Indeed, NDVI and SR showed higher correlations with LAI than MTVI2, which was conceived to remove sensor saturation effects when observing green LAI.

For forest managers interested in LAI, our results suggest that more complex VIs do not offer any advantage over the readily obtainable SR and NDVI. However, sensor saturation restricts the usefulness of spectral-LAI relationships to very young stands with LAI less than 2.

LiDAR metrics

In contrast to the spectral-LAI correlation analysis, all but one of the LiDAR metrics produced significant correlation coefficients (all P-values < 0.05) with measured LAI (Table 4). Indeed, the weakest correlations obtained from the LiDAR metrics were close to the best correlations obtained using VIs. The height related metrics PFAM, ELK, and ECV were highly correlated with LAI (all P-values <0.001). Beets et al.[11] provide the only other examination of LiDAR-LAI models for New Zealand plantation forests. Using the 30th height percentile of returns (P30), in combination with percentage canopy cover, the authors developed models of LAI with an R^2 of 0.88 in 9 year old stands of *P. radiata*. Based on this result, we assessed the correlation between LAI and a variety of height percentiles from our data. Only the 20th height percentile (P20) had a notable association with LAI (r(18)=0.66, P<0.01), while not directly comparable with Beets et al.'s[11] results, the weak correlation did suggest height percentiles may not generalise well to multiple age classes.

The remaining metrics we trialled all utilised ratios between return types as a proxy for canopy penetration. The development of these canopy penetration metrics has been motivated by the apparent connection to the Beer-Lambert law which describes light extinction through a plant canopy[6,12]. Zhao and Popescu[12] found the relatively simple GT, RIGT, and LPM metrics to be strongly related to LAI in a mixed species forest (R^2=0.80-0.83). While Peduzzi et al.[3] found a strong negative correlation (r(107)=-0.75) between LPI and LAI in dense pine plantations. Despite the theoretical links to LAI through the Beer-Lambert law, the penetration metrics showed only modest correlation with LAI in our data. Interestingly, the LPI metric showed the weakest correlation, yet this metric was selected specifically because it had been successfully used to develop LiDAR-LAI models in eastern USA *Pinus taeda* L. plantations[3].

We trialled other penetration metrics (not shown) with stronger theoretical links to the Beer-Lambert law[6] without success. Our results suggest that LiDAR-LAI relationships remain campaign and site specific, and attempts to relate canopy penetration of pulses to the Beer-Lambert law are not yet well developed. Testing the correlation between LAI and a large number of candidate metrics remains the most successful approach.

Despite the lack of a sound theory linking metric selection to LAI, LiDAR shows good potential as a tool for large scale LAI estimation. Our results demonstrate that very simple LiDAR metrics, produced as standard software outputs, showed far higher correlations with LAI than vegetation indices utilising sophisticated sensor technologies and novel spectral domains. Interpreted as a predictive variable, the strength of the relationship between PFAM and LAI would be close to the best single variable LiDAR-LAI relationships observed in this forest type[3].

Table 3. Pearson correlation coefficients for the selected vegetation indices and ground measurements of LAI (n=20). Index descriptions are given in Table 2. Bold italic values were significant at α=0.05.

	LAI	NDVI	SR	GR	VI	gNDVI	NDVIre	SRre	MTVI2	RTVI
LAI	1	***0.46***	***0.48***	0.20	0.10	0.12	0.30	0.28	0.28	0.15
NDVI		1	0.99	0.43	0.02	0.46	0.66	0.63	0.91	0.69
SR			1	0.43	0.02	0.46	0.62	0.61	0.89	0.66
GR				1	-0.84	0.93	0.50	0.50	0.47	0.50
VI					1	-0.87	-0.17	-0.17	-0.08	-0.20
gNDVI						1	0.46	0.45	0.50	0.51
NDVIre							1	1	0.83	0.94
SRre								1	0.82	0.94
MTVI2									1	0.92
RTVI										1

Table 4. Pearson correlation coefficients for the selected LiDAR metrics and ground measurements of LAI (n=20). Metrics are described in Table 1. Bold italic values were significant at α=0.05.

	LAI	PFAM	ELK	ECV	FG_AG	SGR	P30	GT	RIGT	LPI	LPM
LAI	1	***0.85***	***0.83***	***-0.84***	***-0.79***	***-0.78***	***0.56***	***-0.66***	***0.48***	-0.37	***-0.47***
PFAM		1	0.89	-0.88	-0.93	-0.90	0.51	-0.73	0.43	-0.35	-0.43
ELK			1	-0.98	-0.85	-0.84	0.57	-0.72	0.39	-0.38	-0.41
ECV				1	0.88	0.88	-0.70	0.74	-0.38	0.40	0.40
FG_AG					1	0.94	-0.63	0.82	-0.45	0.45	0.48
SGR						1	-0.73	0.84	-0.37	0.49	0.41
P30							1	-0.68	0.16	-0.49	-0.24
GT								1	-0.61	0.80	0.70
RIGT									1	-0.77	-0.97
LPI										1	0.84
LPM											1

Conclusions

These results are promising for the development of LiDAR-LAI models, where covariance between predictors favours parsimony. However, selection of predictive variables for model development requires more sophisticated statistical methods than those undertaken here.

Future work will focus on utilising appropriate statistical methods, with a larger dataset, to develop predictive LiDAR-LAI models suitable for use over large areas and a range of stand conditions.

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