Estimating Leaf Area Index From Terrestrial LiDAR and Satellite Based Vegetation Indices Using Bayesian Inference

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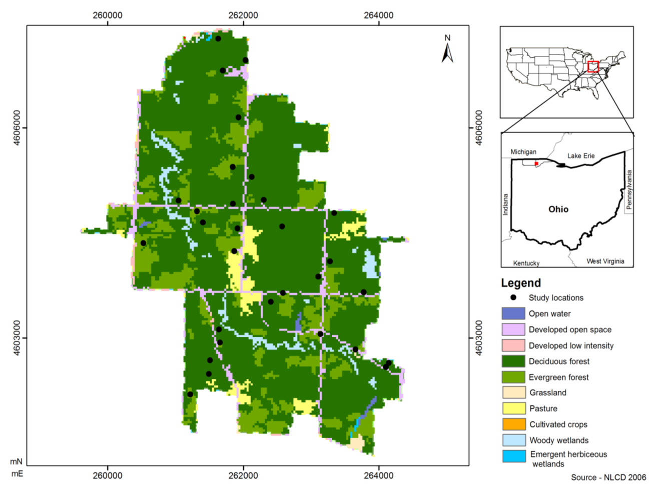
Abstract

Leaf area index (LAI) is an important indicator of ecosystem conditions, and can be estimated in the field using several methods. This study compared LAI estimates from two different sensors, a Leica ScanStation C 10 Terrestrial Laser Scanner (TLS) and a hand-held Li-Cor LAI-2200 Plant Canopy Analyzer (PCA). Our study also evaluated the uncertainty of LAI estimates across space by using remotely sensed vegetation indices. The TLS-based LAI calculation involved separating green leaves from woody biomass based on distance and return intensity. The data were then used with circular and spherical point cloud slicing to calculate stereographically(S) and orthographically(O) projected LAI estimates. The LAI estimates from the TLS and PCA suggested that there is reasonable agreement (i.e., correlations r > 0.50) between the two sensors. Predicted LAI from Landsat TM-based vegetation indices were used to develop a Bayesian Linear Regression (BLR) approach to produce a continuous LAI for the Oak Openings Region in NW Ohio. The results from the BLR provide details about the parameter uncertainties and insight about the potential to estimate LAI using datasets with foliage only in comparison to datasets with foliage and woody biomass. For instance, the modeled residuals associated with the LAI estimates from the TLS orthographic projection that considers only foliage had the lowest overall model uncertainty among all of the LAI estimates. In addition, comparisons between the deviations from the mean of the LAI estimates indicate that sparse and open areas were associated with the highest error.

Study Area

The ground data were collected from 30m radii plots, randomly selected across 30 sites of the Oak Openings Preserve Metro Park, Toledo, a rare ecosystem with an approximate area of 15 km^2 in the Lake Erie watershed.

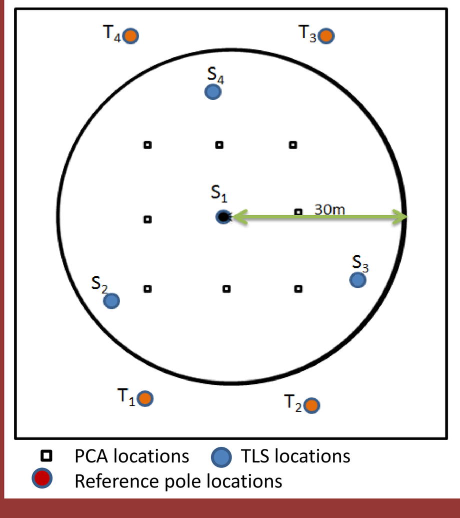


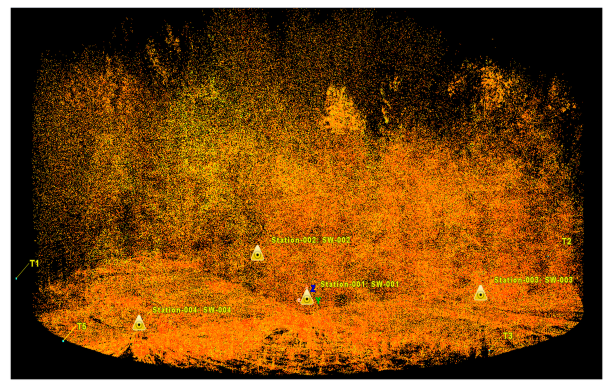
Materials and Methods

Terrestrial Laser Scanner C 10

LAI 2200 Plant Canopy Analyzer (PCA)

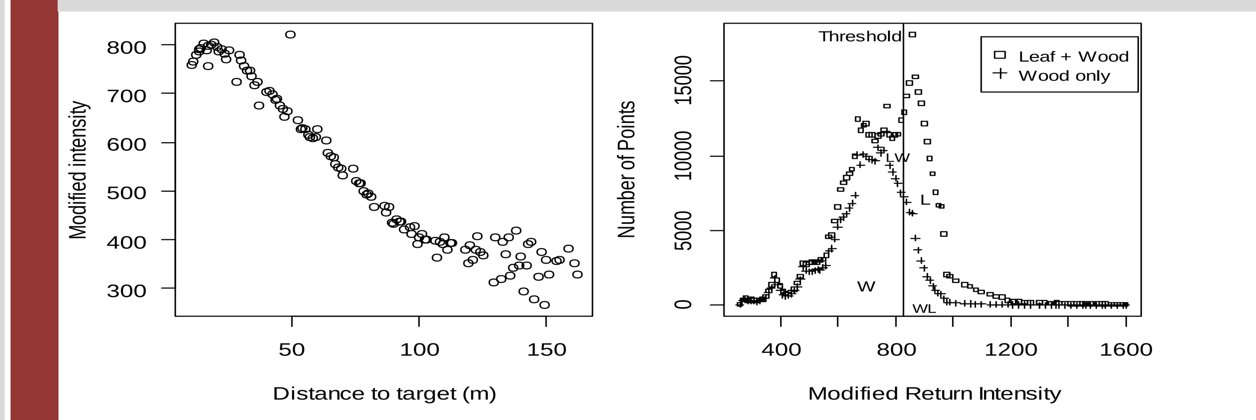
At each site, 4 scans were acquired and co-registered into a single point cloud. The co-registered point clouds were clipped to a 30 m radii surface area. PCA data were collected from 9 positions from each site .



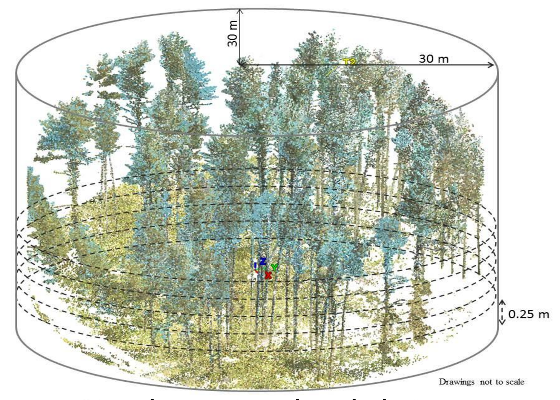


Co-registered 30m radii 3D point cloud

During pre-processing, the TLS return intensity and the distance to the target were identified using both leaf-on and leaf-off scans. Using these results, thresholds separating woody biomass from foliage were detected at 2m distance intervals.

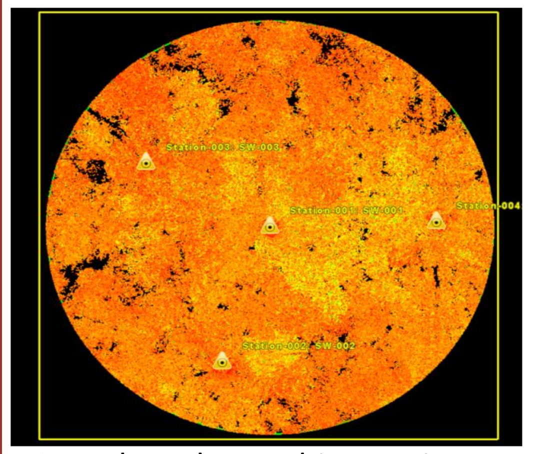


Using thresholds, we prepared two sets of data: data with only foliage and data with foliage and woody biomass. We then calculated LAI from both data sets using stereographic and orthographic projections. To reduce the processing time, each data set was sliced into 25 cm thick slices.

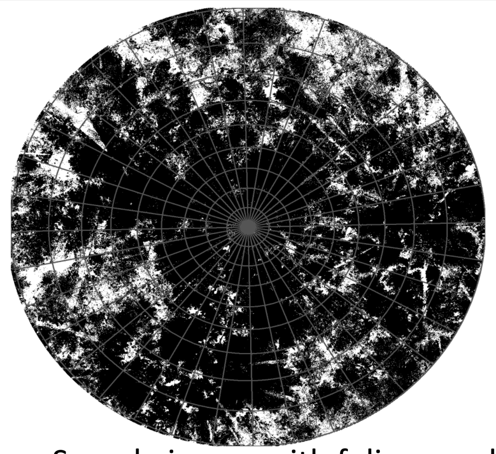


Circular point cloud slicing

Each 25 m slice was projected into a 2D horizontal surface and rasterized into images to calculate Orthographic LAI.

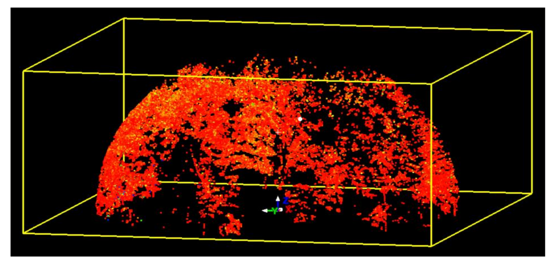


Sample orthographic top view of a point cloud

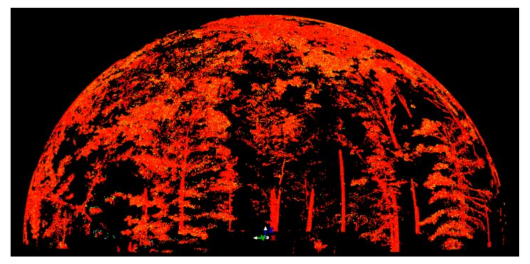


Sample image with foliage and gaps in orthographic view

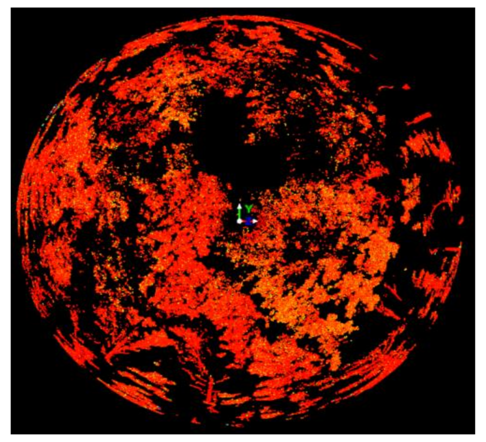
Stereographic LAI was calculated by projecting points to a spherical surface and then to a 2D surface. The points in 2D were rasterized to images.



Points in Cartesian coordinates



Points projected to a surface of a sphere



Stereographic top view

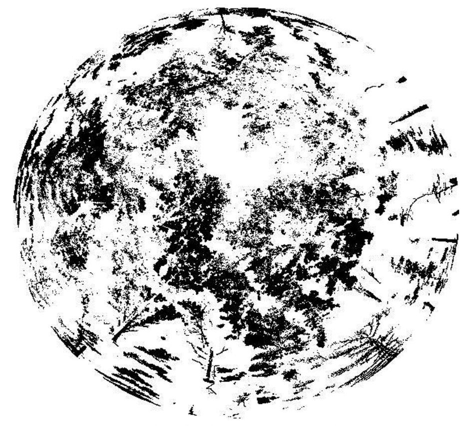
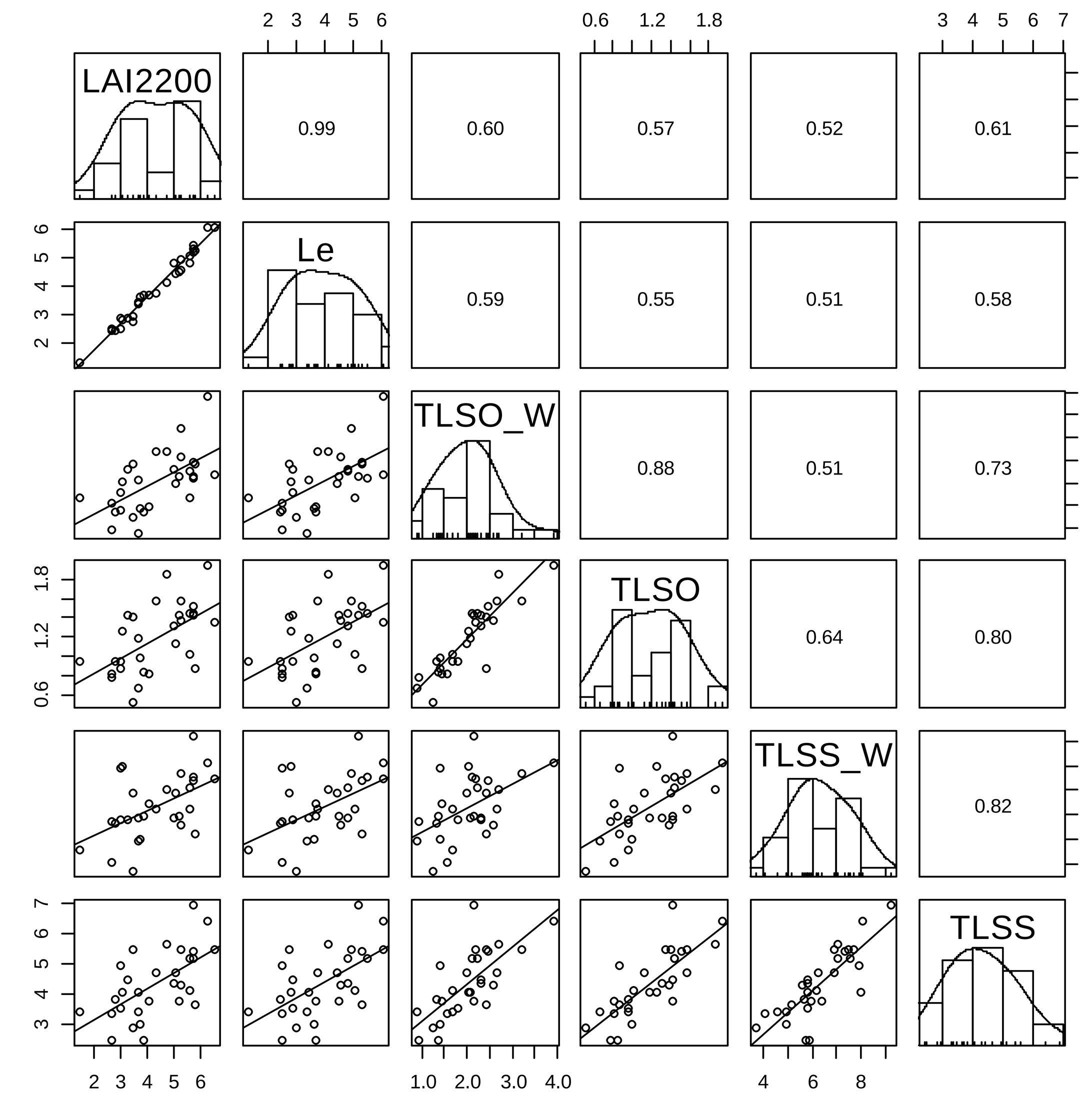


Image with foliage and gaps in stereographic view

Results

High correlations resulted among all LAI estimates from the two sensors.

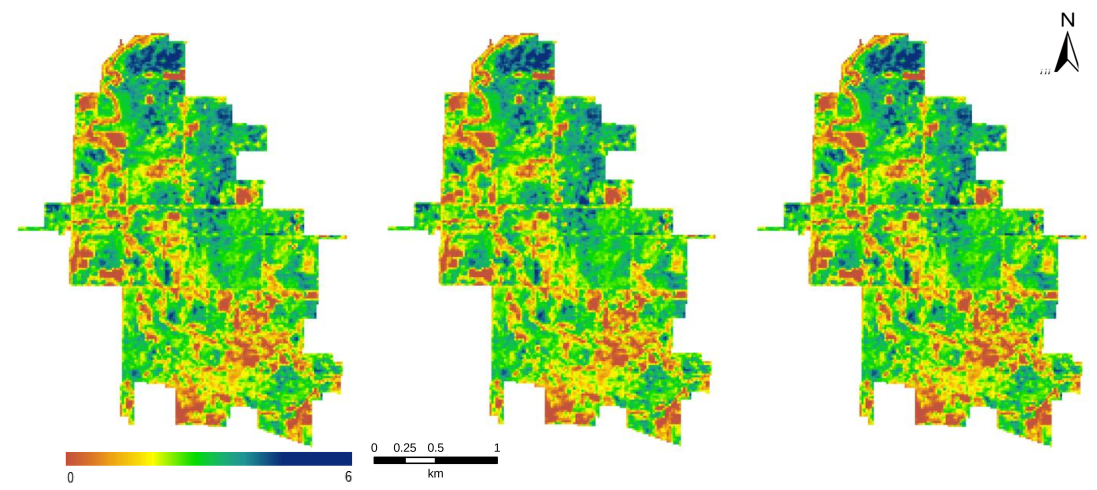
LAI from Plant Canopy Analyzer (PCA)	From TLS orthographic view	From TLS stereographic view
LAI corrected for clumping – LAI2200	Using both foliage + woody biomass - TLSO_W	Using both foliage + woody biomass - TLSS_W
Effective LAI (not corrected for clumping) – Le	Using only foliage - TLSO	Using only foliage - TLSS

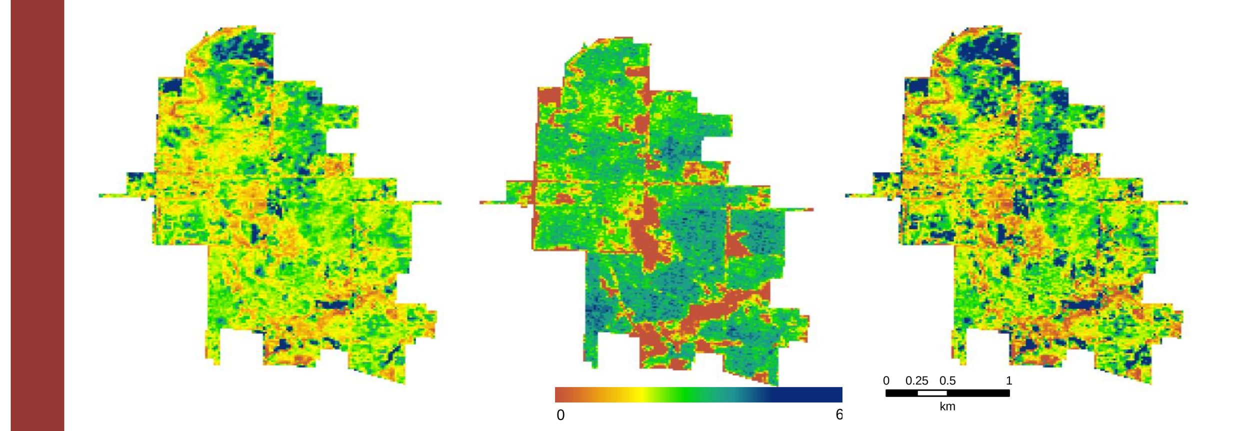


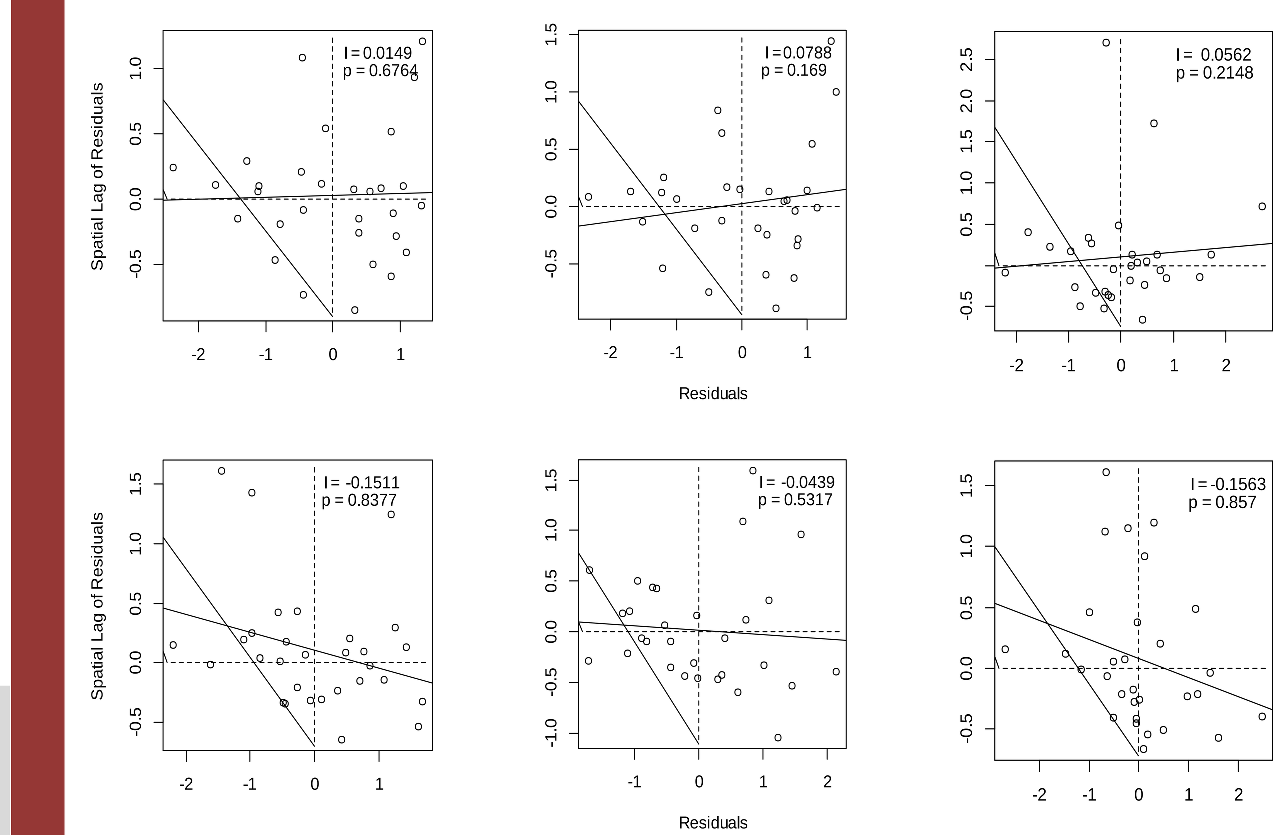
Six models developed from Bayesian Linear Regression (BLR) with Markov chain Monte Carlo simulation using vegetation indices for the six *in-situ* LAIs for the purpose of predicting a continuous spatial LAI. Model uncertainties are also shown using standard deviation (SD).

Parameters	Mean	SD	2.5%	25%	Median	75%	97.5%
Model 1: LAI-2200 = 3.020 + 0.007 * WDVI							
Intercept	3.020	**0.701**	1.60	2.574	3.036	3.486	4.360
WDVI	0.007	**0.004**	0.00	0.005	0.007	0.010	0.015
Model 2: Le = 2.582 + 0.008 * WDVI							
Intercept	2.582	**0.639**	1.288	2.176	2.597	3.007	3.803
WDVI	0.008	**0.003**	0.001	0.005	0.008	0.010	0.015
Model 3: TLSO_W = 1.288 + 0.004 * WDVI							
Intercept	1.288	**0.342**	0.595	1.070	1.295	1.515	1.941
WDVI	0.004	**0.002**	0.001	0.003	0.004	0.005	0.008
Model 4: TLSO = 0.596 + 0.394 * NDVI – 0.511 * SAVI + 0.133 * PVI3							
Intercept	0.596	**0.248**	0.108	0.434	0.597	0.760	1.086
NDVI	0.394	**0.144**	0.107	0.301	0.393	0.493	0.678
SAVI	-0.511	**0.188**	-0.881	-0.640	-0.509	-0.390	-0.138
PVI3	0.133	**0.048**	0.037	0.102	0.133	0.166	0.229
Model 5: TLSS_W = 3.752 + 0.006 * DVI + 0.008 * SAVI							
Intercept	3.752	**0.907**	1.980	3.158	3.757	4.357	5.521
DVI	0.006	**0.004**	-0.001	0.004	0.006	0.009	0.013
SAVI	0.008	**0.004**	0.000	0.006	0.008	0.011	0.016
Model 6: TLSS = 2.493 + 1.349 * NDVI - 1.747 * SAVI + 0.452 * PVI3							
Intercept	2.493	**0.790**	0.934	1.973	2.494	3.013	4.055
NDVI	1.349	**0.460**	0.434	1.051	1.344	1.664	2.256
SAVI	-1.747	**0.599**	-2.928	-2.157	-1.741	-1.360	-0.556
PVI3	0.452	**0.154**	0.145	0.352	0.450	0.558	0.756

Continuous estimates of LAI for the study area using BLR mean values for (a) Model 1, (b) Model 2, (c) Model 3, (d) Model 4, (e) Model 5; and (f) Model 6.







Plots of Moran's *I* test indicate that there is no spatial autocorrelation among model residuals of (a) LAI 2200 (b) Le (c) TLSO_W (d) TLSO (e) TLSS_W, and (f) TLSS.

Conclusions

- Correlations among the six calculated LAIs suggest that there is a strong agreement between the two sensors (TLS and LAI 2200 PCA).
- The BLR models suggest that the model complexity increases for LAI predictions of foliage compared to the prediction using both foliage and wood biomass.
- The Bayesian Inference uncertainties and modeled residuals conclude that LAI estimates from the TLS orthographic projection that consider only foliage had the lowest overall model uncertainty with lowest error and residual dispersion range among the six spatial LAI estimating models.
- TLS point cloud data can provide LAI estimates of foliage, potentially saving time and providing a more comprehensive dataset than other field-based methods.

References

1. Asner, G. P., Scurlock, J. M., & A Hicke, J. (2003). Global synthesis of leaf area index observations: implications for ecological and remote sensing studies. *Global Ecology and Biogeography*, *12*(3), 191-205.
2. Chasmer, L., Hopkinson, C., & Treitz, P. (2006). Investigating laser pulse penetration through a conifer canopy by integrating airborne and terrestrial lidar. *Canadian Journal of Remote Sensing*, *32*(2), 116-125.
3. Foody, G. M., & Atkinson, P. M. (Eds.). (2002). *Uncertainty in Remote Sensing and GIS*. Chichester:John Wiley & Sons.
4. Gorsevski, P. V. (2013). Using Bayesian inference to account for uncertainty in parameter estimates in modelled invasive flowering rush. *Remote Sensing Letters*, *4*(3), 279-287.
5. Hosoi, F., & Omasa, K. (2007). Factors contributing to accuracy in the estimation of the woody canopy leaf area density profile using 3D portable Lidar imaging. *Journal of Experimental Botany*, *58*(12), 3463-3473.
6. Moskal, L. M., & Zheng, G. (2011). Retrieving forest inventory variables with terrestrial laser scanning (TLS) in urban heterogeneous forest. *Remote Sensing*, *4*(1), 1-20.

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