Estimation of big sagebrush leaf area index with terrestrial laser scanning

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Abstract

Accurate monitoring and quantification of the structure and function of semiarid ecosystems is necessary to improve carbon and water flux models that help describe how these systems will respond in the future. The leaf area index (LAI, m^2 m^{-2}) is an important indicator of energy, water, and carbon exchange between vegetation and the atmosphere. Remote sensing techniques are frequently used to estimate LAI, and can provide users with scalable measurements of vegetation structure and function. We tested terrestrial laser scanning (TLS) techniques to estimate LAI using structural variables such as height, canopy cover, and volume for 42 Wyoming big sagebrush (*Artemisia tridentata* subsp. *wyomingensis* Beetle & Young) shrubs across three study sites in the Snake River Plain, Idaho, USA. The TLS-derived variables were regressed against sagebrush LAI estimates calculated using specific leaf area measurements, and compared with point-intercept sampling, a field method of estimating LAI. Canopy cover estimated with the TLS data proved to be a good predictor of LAI (r^2 = 0.73). Similarly, a convex hull approach to estimate volume of the shrubs from the TLS data also strongly predicted LAI (r^2 = 0.76), and compared favorably to point-intercept sampling (r^2 = 0.78), a field-based method used in rangelands. These results, coupled with the relative ease-of-use of TLS, suggest that TLS is a promising tool for measuring LAI at the shrub-level. Further work should examine the structural measures in other similar shrublands that are relevant for upscaling LAI to the plot-level (i.e., hectare) using data from TLS and/or airborne laser scanning and to regional levels using satellite-based remote sensing.

Keywords: *Artemisia tridentata*, convex hull volume, ground-based LiDAR, leaf area index, terrestrial laser scanning, voxel volume

1. Introduction

Dryland ecosystems, including grasslands, shrublands, and savannas, occupy roughly 40% of the Earth's land surface (Meigs, 1953) and are particularly sensitive to climate and land use change (Backlund et al., 2008). Vegetation dynamics in dryland ecosystems such as the sagebrush-steppe in the Great Basin of the United States will likely be affected by climate change through elevated levels of CO_2, changes in air temperature, and the timing and distribution of precipitation (Bates et al., 2006; Kwon et al., 2008). In turn, woody plants such as sagebrush exert a major influence on dryland ecosystem processes such as evapotranspiration and carbon and nutrient cycling (Breshears, 2006; Yang, J. et al., 2012). Water and carbon fluxes in sagebrush are strongly related to plant leaf area index (LAI), a biophysical measure of the layers of leafy vegetation and an indicator of photosynthetic activity and net primary production (Bonan, 1993; Bussotti and Pollastrini, 2015; Smith et al., 1990). Changes in water and carbon cycling of the sagebrush-steppe in response to climate change will ultimately have land management consequences related to forage production, habitat quality and other ecosystem services (Polley et al., 2013). Importantly, measurement or accurate estimation of LAI is necessary for modeling and understanding water and carbon cycling in the sagebrush-steppe.

Due to their vast areal extent across North America, sagebrush (*Artemisia tridentata* Beetle)-dominated rangelands potentially represent a substantial carbon sink (Hunt Jr. et al., 2003; Prater and DeLucia, 2006). Understanding the spatiotemporal variability in sagebrush LAI is important for accurately predicting carbon budgets, even at the global scale (e.g., with global circulation models [GCMs]), under current and climate-change scenarios. Even within subspecies (e.g., Wyoming big sagebrush, *Artemisia tridentata* subsp. *wyomingensis* Beetle & Young), sagebrush LAI likely varies among plants, stands, and even regions as well as among seasons and years. Data sets of sagebrush LAI for extensive areas and differing seasons are scarce because shrub LAI data are difficult and expensive to acquire with conventional field techniques (e.g., point-intercept sampling, light-intercept sensors, or destructive leaf harvest) and linkages that would promote upscaling between field measures and remotely-sensed estimates have not been established for shrublands (Hufkens et al., 2008). Consequently, accurate modeling of the spatiotemporal variability of sagebrush LAI is inhibited by a paucity of data to develop and validate such models over space and time. Without a better understanding of this spatiotemporal variability in sagebrush leaf area, accurate predictions of climate-change effects on sagebrush itself, and on water and carbon flux responses in sagebrush-dominated rangelands are not possible.

Efficient and accurate assessment techniques are important for facilitating sagebrush LAI data collection over extensive areas and among differing time periods. Many methods have been developed to estimate LAI in a variety of ecosystems. The most accurate estimates come from direct measurements that require destructive sampling (Beerling and Fry, 1990). Despite the advantages in increased accuracy with destructive sampling, it is time-intensive and impractical at scales relevant to modeling the impacts of climate change. Other direct measurements involve developing allometric equations related to easily measured vegetation characteristics such as height or canopy cover, or field techniques such as point-intercept sampling (Bonham, 1989; Clark and Seyfried, 2001). Indirect measurements usually involve light interception techniques with hemispherical photography (Jonckheere et al., 2004), or commercially available instruments such as the Li-Cor® LAI-2000 Plant Canopy Analyzer (Mussche et al., 2001). However, indirect estimates have proven challenging in sagebrush-dominated ecosystems because light is disproportionately blocked by woody plant material, which leads to overestimation of LAI (Finzel et al., 2012).

Satellite remote sensing studies have demonstrated direct relationships between LAI and vegetation indices (Danson et al., 2003; Qi et al., 2000) such as the normalized difference vegetation index (NDVI) and the modified soil-adjusted vegetation index (MSAVI, Qi et al., 1994). These spectral indices leverage biophysical knowledge of the “red-edge” where photosynthetic absorption in the red spectrum and high reflectivity in the near-infrared correlate to green, leafy biomass or LAI (Turner et al., 1999). However, the relationship between vegetation indices and LAI breaks down in species with a large woody component (Hunt Jr. et al., 2003) and in dryland ecosystems in general because they contain weak vegetation signals overpowered by high soil reflectance and complex scattering (Kremer and Running, 1993; Mundt et al., 2006; Okin et al., 2001; Qi et al., 1994).

Terrestrial laser scanning (TLS) provides some advantages over standard field techniques for measuring or estimating sagebrush LAI, such as offering a link between ground-based measurements and airborne remotely-sensed estimates (Hopkinson et al., 2013; Vierling et al., 2013) and reduced personnel time cost per unit area sampled. Consequently, TLS could provide an effective means of acquiring the sagebrush LAI data needed to scale to satellite-based remote sensing and thus properly develop and validate ecological and hydrological models required to accurately understand and predict the consequences of climate change. To investigate the use of TLS for estimating LAI of Wyoming big sagebrush, a dominant sagebrush subspecies in the Great Basin, we: (1) assess the accuracy of using TLS data to derive vegetation metrics for estimating sagebrush LAI by comparing TLS metrics to those derived from destructive harvesting and leaf area field measurements; and (2) contrast the accuracy of the TLS-derived sagebrush LAI with the field tested method of point-intercept sampling across three study sites in the Snake River Plain, Idaho, USA.

2. Methods

2.1. Study Area

The study was conducted at three sites across the Snake River Plain in southern Idaho, USA that are characteristic of the Snake River Plain and Northern Basin and Range ecoregions of the Great Basin; Reynolds Creek Experimental Watershed (RCEW), Hollister, and Snaky Canyon Wash (SCW). These sagebrush-grassland sites are dominated by Wyoming big sagebrush, bluebunch wheatgrass (*Pseudoroegneria spicata* A. Löve), and Sandberg bluegrass (*Poa secunda* J. Presl). The RCEW study site is located in Owyhee County (43°10’32”N, 116°43’2”W; elevation: 1367 m) and has average annual precipitation of 271 mm and mean annual air temperature of 8.8 °C. Soils at RCEW consist of well-drained gravelly and silt loams from the Willhill-Cottle-Longcreek and Arbidge-Owsel-Gariper soil series complexes. The Hollister study site (Twin Falls County, Idaho, USA; 42°18’58”N, 114°41’34”W; elevation: 1448 m) has average annual precipitation of 256 mm and mean annual temperature of 8.8 °C. The soil at Hollister is well-drained and consists of Chuska very stony loam and Shabliss silt loam. The SCW study site (Clark County, Idaho, USA; 44°4’23”N, 112°38’14”W; elevation: 1529 m) has average annual precipitation of 206 mm, and mean annual temperature of 6.5 °C. Soils at SCW are somewhat excessively drained, gravelly loams from a complex of the Whitecloud, Simeroi, and Paint soil series. Climate data were sourced from the Western Regional Climate Center operated by the Desert Research Institute (WRCC, 2009), and soil data from Web Soil Survey of the Natural Resources Conservation Service (Soil Survey Staff, 2013).

2.2. Field Sampling

Terrestrial laser scanning, LAI point-intercept measurements, and destructive biomass sampling of Wyoming big sagebrush (hereafter referred to as sagebrush) was conducted at RCEW, Hollister and SCW from September to October 2012. Terrestrial laser scanning and destructive biomass sampling methods are detailed in Olsoy et al. (2014). Scanning was performed with a Riegl VZ-1000 TLS instrument with a 1550 nm near-infrared laser with waveform processing, 8 mm accuracy at 100 m range (Riegl, 2015), and a beam diameter of 2 mm at 6.67 m range (Yang, R. et al., 2012). Three plots were established at each study site and each plot contained two 25 m^2 sub-plots. The sub-plots all included two or three marked sagebrush (n = 15 per site, total n = 45) and were scanned from two opposing scan positions at a mean distance of 5.7 m from each sagebrush plant with laser pulse rate set to 300 kHz and an angular stepwidth of 0.01°, resulting in a minimum point spacing of 2 mm (**Fig. 1**). Scans were georeferenced using four reflective targets whose positions were captured using a survey-grade

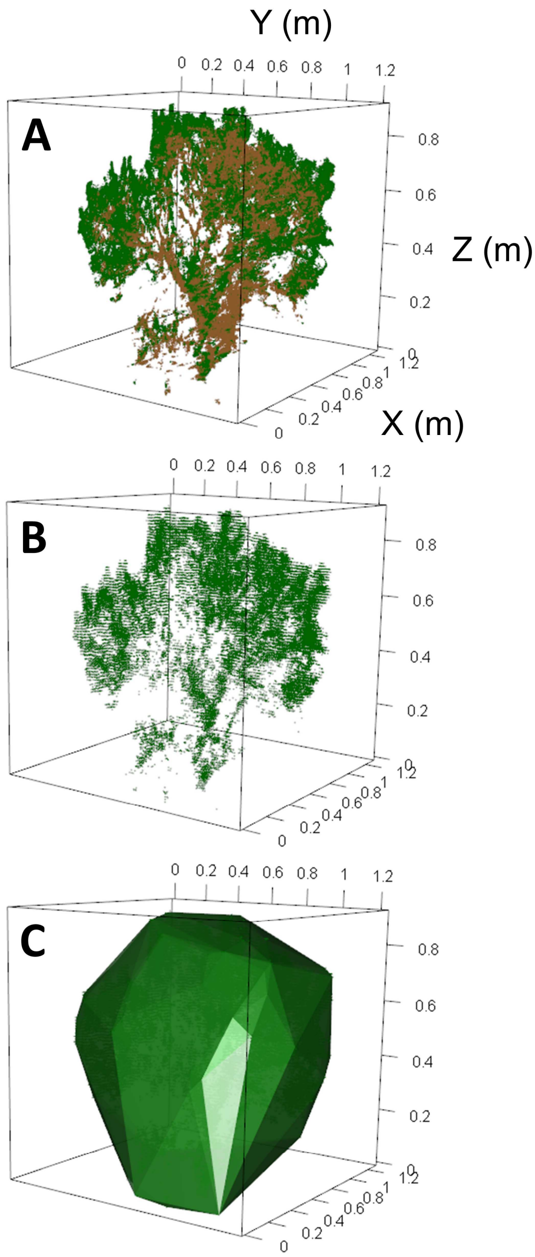

Figure 1. Point cloud of a sagebrush with green and non-green classified points (**A**); voxelized green volume (**B**); and convex hull green volume (**C**).

GPS unit. After scanning the sub-plots, a 1-m^2 quadrat (n = 42) was fit around each sagebrush within the sub-plots and point-intercept sampling was applied to estimate LAI (Clark and Seyfried, 2001). The sagebrush LAI point-intercept sampling approach uses a 20-pin frame with five equally spaced frame locations within the 1 m^2 quadrat for a total of 100 attempts m^{-2}. This method uses a sharpened pin that is pushed through the sagebrush canopy and one records the number of pin-point contacts or "hits" with green foliage. The number of green hits is divided by the number of attempts to give an estimate of LAI (**Fig. 2**). Multiple point frames may be used for shrubs larger than 1 m^2. However, in this study, shrubs that did not fit within a single quadrat (i.e., > 1 m^2) were excluded from the LAI analysis due to limitations of comparing multiple point frames with metrics from a single TLS point cloud.

After point-intercept sampling, each sagebrush was destructively sampled by cutting the sagebrush at ground-level and collecting the plant matter into plastic bags for temporary storage. All samples were sorted to separate the green biomass; which included leaves, green stems, and seeds, from the woody biomass. The sorted samples were oven-dried at 65 °C for 48 h or until a constant dry weight was reached and recorded. The biomass of the green and woody components were recorded separately for each sagebrush plant (Olsoy et al., 2014).

In January and February 2014, sagebrush leaves were collected at the three sites to obtain site-wide specific leaf area (cm^2 g^{-1}, SLA) for estimation of LAI from field-measured biomass. The sagebrush leaf data collection consisted of collecting a total of 400 fresh leaves from each study site. For each study site, 100 leaves were collected at random from multiple shrubs (5–15 shrubs) at each of the three plots and an additional 100 leaves were randomly collected from all of the combined plots. The combined sample for each study site was maintained separately and later used to independently validate mean SLA values.

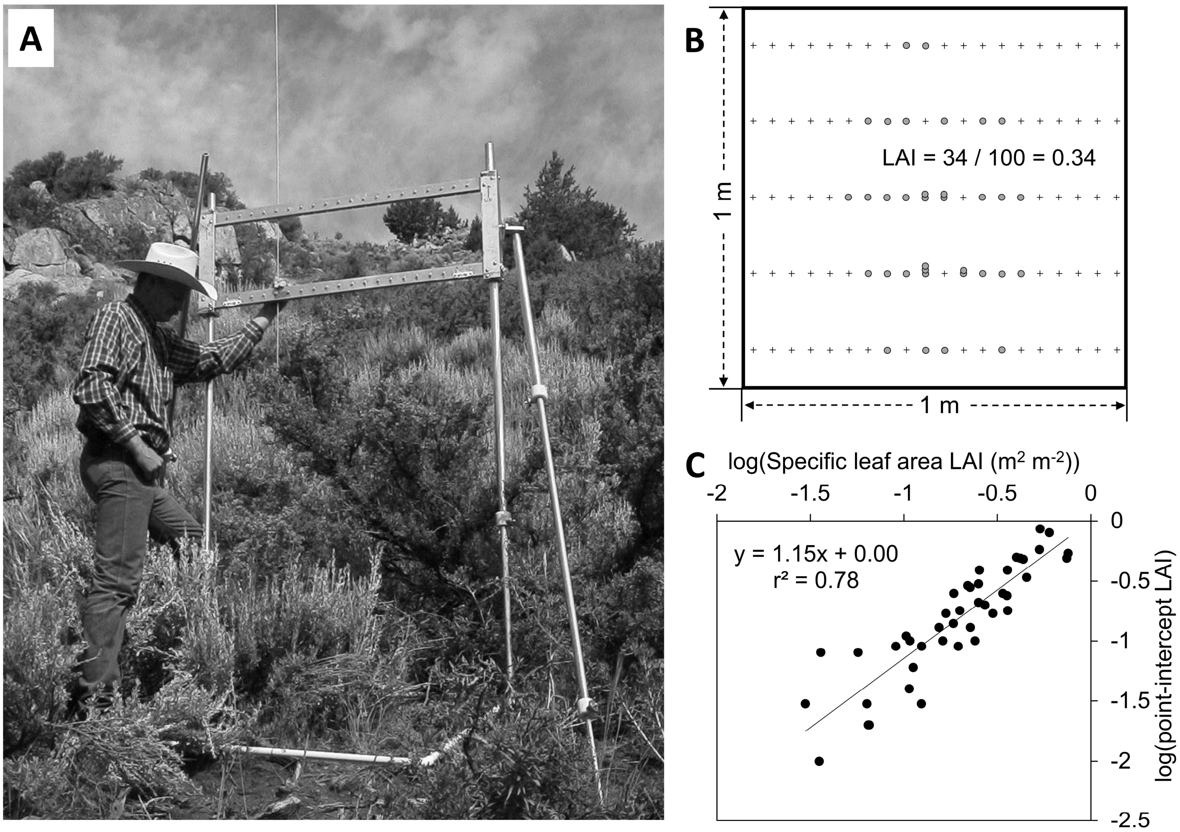

Figure 2. Photo of point-intercept sampling being performed in the field (**A**). A schematic showing the number of attempted pin-point hits (crosses) in a 1 m^2 quadrat with theoretical distribution of green hits (grey circles) (**B**). Regression results for point-intercept LAI plotted against specific leaf area LAI (**C**).

2.3. Lab Analysis

Sagebrush specific leaf area was calculated for shrubs located at all nine of the plots (RCEW, Hollister, and SCW) following standard procedures outlined by Breda (2003). Briefly, a sub-sample of leaves collected from sagebrush plants at the study sites were used to calculate SLA, which is a site-specific ratio of leaf area to dry leaf biomass (Chiarriello et al., 1989). Multiplying the measured dry leaf biomass of a plant by the site-specific SLA provides an estimate of leaf area for each sampled plant.

Collected leaves were stored at 0 °C until processed 1–2 days later. The total surface area (cm^2) of all collected leaves for each individual or combination plot was determined with a Li-Cor 3100 Leaf Area Meter (1 mm^2 resolution) with an error of ±1% for a 10 cm^2 area. The leaf area meter was calibrated with the factory supplied calibration disk between runs. The leaf samples were bagged by plot, oven-dried in a laboratory-grade gravity convection oven for 48 h at 80 °C, and weighed to the nearest thousandth of a gram. The SLA of each plot was then calculated as the quotient of surface area and oven-dry weight. The site-specific SLA values were multiplied by the green biomass dry-weight of each sagebrush plant to obtain an estimated leaf area and divided by the sampled ground surface area to convert into a dimensionless parameter of LAI. The point-intercept LAI estimates and TLS-derived vegetation metrics were then compared to this SLA-derived LAI estimate.

Specific leaf area is often used as an indicator of photosynthetic efficiency or resource allocation by plants (Reekie and Reekie, 1991). Stressors such as low water availability and animal browsing can cause plants to compromise between photosynthesis and growth (Hoffman and Wambolt, 1996). We assumed that SLA would not differ between 2012, when field sampling was performed, and 2014, when SLA sampling was performed. This assumption is similar to another study which considered SLA to be consistent at a site across different years (e.g., Turner et al., 1999). SLA is largely governed by site-specific properties, such as soil fertility, solar insolation, and precipitation (Ackerly et al., 2002; Ordoñez et al., 2009), which may differ between years.

2.4. TLS Analysis

The scans from the TLS were registered together in RiSCAN Pro software (Riegl Laser Measurement Systems GmbH, Horn, Austria). Each shrub was manually delineated to remove laser hits or points on the ground surface and on non-target vegetation. The point cloud was post-processed to remove noisy points that represent partial or false returns using a Riegl-specific metric referred to as "deviation", which is a measure of the difference in pulse shape of the laser return compared to the emitted pulse (Greaves et al., 2015; Pfennigbauer, 2010). All points were used to calculate shrub height and canopy cover. We determined canopy cover by calculating the percent of the ground surface covered using a minimum convex polygon of the TLS points. Shrub height and canopy cover were multiplied together as an alternative to voxel and convex hull volume. The remaining points were classified using the methods described in Olsoy et al. (2014), where points with laser-reflectance values below a given threshold are classified as green, or photosynthetically active (see also Beland et al., (2014) for similar TLS reflectance-based classification of leaf points). The subset of green-classified points was then used to calculate canopy volume using a voxel-based approach and a 3-D convex hull approach (Olsoy et al., 2014). Voxels are volumetric pixels of a given size (e.g., 1 cm^3) that are either counted (1) or not (0) based on whether they contain points (Greaves et al., 2015; Hosoi and Omasa, 2006; Olsoy et al., 2014). The convex hull approach uses the outermost set of points to create a volume (Barber et al., 1996; Olsoy et al., 2014). These two approaches alternatively provide a minimum (voxels, **Fig. 1B**) and maximum (convex hull, **Fig. 1C**) volume for each plant. Finally, the green-classified points were also multiplied by the average beam area to obtain a direct estimate of TLS leaf area (m^2). The average beam area for each sagebrush was estimated based on the distance between the plant and the scanner and assuming a uniform beam divergence for each plant.

2.5. Statistical Analysis

To compare the accuracy of TLS-derived metrics to point-intercept sampling, each variable (height, canopy cover, volume, and TLS leaf area) was regressed against the SLA-derived LAI estimate (SLA LAI). In all cases, the residuals and variance were non-normal, therefore both the response and independent variables were log-log transformed giving (**Eq. 1**):

$$\log(L) = k\log(x) + a$$

where, *L* is SLA LAI, *k* and *a* are the regression slope and intercept parameters, and *x* is the independent variable. Back-transforming gives the power law equation (**Eq. 2**):

$$L = 10^a x^k$$

Power law equations are frequently found in biological systems with allometric scaling (Enquist et al., 1998). For example, sagebrush and global inflorescence biomass have been compared to stem and leaf biomass using log-log transformations of the data (Cleary et al., 2008). Another example is a common allometric function - the logarithmic relations between diameter at breast height or basal area and leaf area index, which produces a power law relation between mass per dry weight or area and stem diameter (Gower et al., 1999; Levia, 2008; Whittaker and Woodwell, 1967).

An analysis of variance (ANOVA) was used to test the site-specificity of our sagebrush SLA measurements at our three study sites across the Snake River Plain. All statistical tests were performed with the R statistical package (R Core Team, 2013). Test assumptions were evaluated with a Shapiro-Wilk normality test and a Bartlett test of homogeneity of variance. The one-way ANOVA test determined if the means at the sites were all equal, and a Tukey's honest significant difference test was then used to further analyze which pairs of means differed from each other.

3. Results and Discussion

3.1. Specific Leaf Area

Specific leaf area values at Hollister (42.3 ± 3.93 cm^2g^{-1}) and SCW (42.2 ± 6.49 cm^2g^{-1}) were larger than at RCEW (30.1 ± 2.03 cm^2g^{-1}; $P = 0.025$). Specific leaf area was thus found to be site-specific for sagebrush, similar to previous studies. For example, a study of sagebrush in Yellowstone National Park reported SLA of 45.2 – 54.6 cm^2g^{-1} (Hoffman and Wambolt, 1996). Another dryland shrub, *Retama sphaerocarpa* (Boiss.), had SLA ranging from about 14 to 16 cm^2g^{-1} (Pugnaire et al., 1996). The lower SLA values at RCEW indicate thicker leaves, which contributes to a longer leaf life span, improved nutrient retention and protection of the leaves from desiccation (Ackerly et al., 2002; Poorter and Remkes, 1990). These plant adaptations may dampen the turnover of evapotranspiration (ET), which has been reported to return as much as 90% of incoming precipitation to the atmosphere (Branson et al., 1976; Flerchinger et al., 1996; Wight et al., 1986). Overall, the significant differences in SLA in this study are likely attributed to some combination of differences in genetic variation, phenological development and environmental factors (e.g., microhabitat features) across the study sites. Ongoing work at the Hollister and RCEW sites includes more intensive SLA sampling that is concurrent with airborne hyperspectral (AVIRIS-NG) image acquisitions to explore spectral estimates of SLA on a per pixel basis. Several recent studies have demonstrated the use of spectral data collected or simulated at the leaf scale to estimate SLA in boreal forests (Serbin et al., 2014), leaf mass per unit area (the inverse of SLA) across a range of species (Cheng et. al., 2014) and live fuel moisture content and leaf dry mass in sagebrush (Qi et al., 2014). While sagebrush SLA values also fluctuate seasonally, future studies could minimize the influence of forbs and grasses on shrub LAI estimation error by sampling in late summer and early fall after senescence.

3.2. LAI Estimation

TLS-derived vegetation metrics and field-based point-intercept sampling performed similarly well when compared against SLA-derived LAI as a standard (**Figs. 2C and 3**). Canopy volumetric estimates derived from TLS performed well when regressed against SLA LAI, with 3-D convex hull providing the highest estimates ($r^2 = 0.76$, **Fig. 3F**), while 1 cm^3 voxel volume explained 61% of the variation ($r^2 = 0.61$, **Fig. 3E**). Shrub height estimates were a relatively poor predictor of LAI ($r^2 = 0.47$, **Fig. 3A**) compared to canopy cover ($r^2 = 0.73$, **Fig. 3B**). Multiplying shrub height and canopy cover together provided no added benefit over canopy cover alone ($r^2 = 0.73$, **Fig. 3C**). A direct estimate of leaf area from the green-classified points explained 65% of the variation in SLA LAI ($r^2 = 0.65$, **Fig. 3D**). Finally, point-intercept sampling explained almost 80% of the variation ($r^2 = 0.78$, **Fig. 2C**). Clark and Seyfried (2001) found similar results in sagebrush communities using point-intercept sampling with vertical pins ($r^2 = 0.82$). The direct estimate using green-classified points may have been less effective than expected due to incomplete penetration of the TLS into the shrub canopy. In addition, one potential reason that TLS-derived convex hull volume did not improve on point-intercept sampling is that the volumetric measurement provided by the convex hull does not account for within canopy variation. This could be problematic for larger shrubs, which were excluded from our analysis. Therefore, study sites with a dominance of larger shrubs (> 1 m^2) require further validation and possibly the use of other volumetric methods.

Voxel size must be chosen with consideration of beam diameter, leaf size, and distribution of leaves (Beland et al., 2014; Cifuentes et al., 2014; García et al., 2015). Greaves et al. (2015) demonstrated that slightly larger voxels (3-5 cm, $R^2 > 0.9$) from TLS greatly improved biomass estimation of two arctic shrub species (*Salix pulchra* Cham. and *Betula nana* L.) in northern Alaska compared to 1 cm^3 voxels ($R^2 = 0.38$). Further, Greaves et al. (2015) found that for variable-range point clouds, a volume differencing approach was more effective than voxel counting. However, Hosoi and Omasa (2007) used smaller 5 mm voxels with TLS to successfully model leaf area density throughout the canopy of a mixed tree plantation in Tokyo, Japan, with mean absolute error of 12.7% when measurement zenith angle was 90° compared to 57% error at 71°, suggesting that incidence angle may be just as important as voxel size. Beland et al. (2014) recommended voxels approximately 10 times the leaf size to minimize occlusion while retaining the detailed structural information inherent to TLS data.

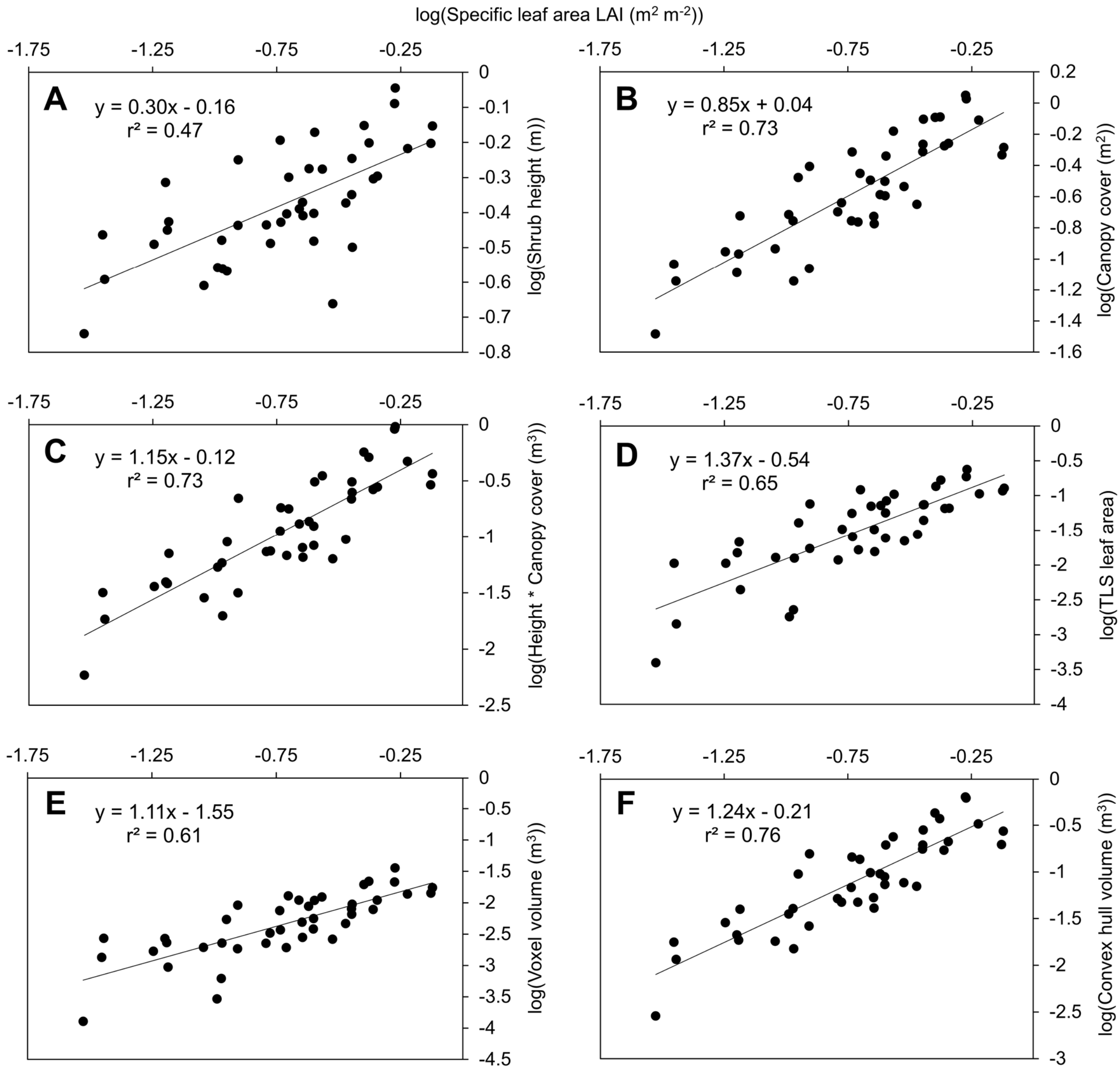

Figure 3. Log-log regression equations and r^2 values for prediction of specific leaf area (SLA) derived leaf area index (LAI) by terrestrial laser scanning (TLS) derived metrics: A) shrub height, B) canopy cover, C) height * canopy cover, D) TLS leaf area, E) voxel volume, and F) convex hull volume.

However, the convex hull and point-intercept sampling methods provided comparable results and this demonstrates the fine-scale capabilities of the TLS and the capacity to replace time-consuming field techniques. TLS also has the potential to scale from field to airborne or satellite-based measurements. The TLS provides point data similar to point-intercept sampling, yet uses the same technology and delivers a similar 3-D point cloud to airborne laser scanning (ALS). TLS could be used as ground validation for ALS, in which simple metrics such as vegetation height (Luo et al., 2015) or percent vegetation cover can be calculated from lower density ALS data, and could be used for future work estimating sagebrush LAI across the landscape. For example, Mitchell et al. (2011) found height and canopy cover for sagebrush were consistently underestimated when using moderate resolution ALS data (9.46 pts m^{-2}) but with compensation, accurate estimates of both shrub height (r^2 = 0.86) and canopy cover (r^2 = 0.78) could be obtained. A hierarchical method linking ground estimates to TLS, and TLS to ALS, may provide the ability to scale up from the plot to the watershed level (Li et al., 2015). Further, as ALS technology improves to higher point densities, volume measurements will become more accurate (Vierling et al., 2013) and more viable for estimating plant characteristics such as LAI and biomass.

Monitoring of vegetation structure and function at the plot-level (i.e., hectare) and landscape-level (i.e., tens to hundreds of km^2) may also be accomplished with a combination of spectral and structural remote-sensing data. Estimation of vegetation characteristics in dryland ecosystems with spectral information alone (e.g., Landsat multispectral or AVIRIS hyperspectral data) has proven difficult due to high levels of land cover heterogeneity and pixel mixing (Okin et al., 2001). Yet, hyperspectral imagery with up to a hundred or more spectral bands has been shown to be useful, especially when combined with structural information from ALS (Mitchell et al., 2015). For species-specific parameters, hyperspectral imagery can provide species-level classification and top of canopy spectral information, while TLS or ALS provides the structural information necessary to capture multiple levels of canopy structure. Correspondingly, TLS-derived LAI could readily promote estimates of photosynthesis and evapotranspiration, which are crucial variables for climate change research. For example, within and between seasonal changes in LAI might be obtained by TLS due to its portability and relative ease-of-use in the field. These changes of LAI over time could then be used to estimate how evapotranspiration of sagebrush communities change in the context of warming (Polley et al., 2013). Furthermore LAI, coupled with measurements of vegetation function, such as nitrogen from hyperspectral data will help model CO_2 uptake in these systems (Mitchell et al., 2012). Expanded ground-based LAI measurements in dryland shrub environments will improve our ability to develop and estimate LAI products at the airborne and satellite scales. Spatially-explicit models of LAI, derived from laser data acquired at these broader scales, can help with reducing uncertainties associated with carbon and water flux models in drylands and detecting subtle ecosystem responses to disturbance over time.

3.3. Conclusions

Findings from this study support those at other sites and with other shrub species, which indicate SLA can be site specific. Consequently, SLA sampling is advisable for new sites, particularly those in differing climatic and edaphic conditions, rather than simply accepting and applying published average values. More importantly, we demonstrated that models involving TLS-derived canopy volume, canopy cover, or laser-reflectance values (i.e., green vs. non-green points) can explain 65-76% of the variance in SLA-derived LAI of sagebrush. A 3-D convex hull analysis provided the most accurate prediction ($r^2 = 0.76$) of SLA-derived LAI using TLS data. This performance was quite similar to that obtained using a traditional field technique, point-intercept sampling but at what is likely a substantial reduction in field-time costs.

These results, coupled with previous studies (e.g., Greaves et al., 2015; Olsoy et al., 2014) suggest that TLS is a promising technology for quantifying vegetation structure in shrub-dominated landscapes. With further validation of larger shrubs (e.g. > 1 m^2) and additional woody species, TLS may be a rapid and accurate tool for indirectly measuring LAI in dryland shrub environments.

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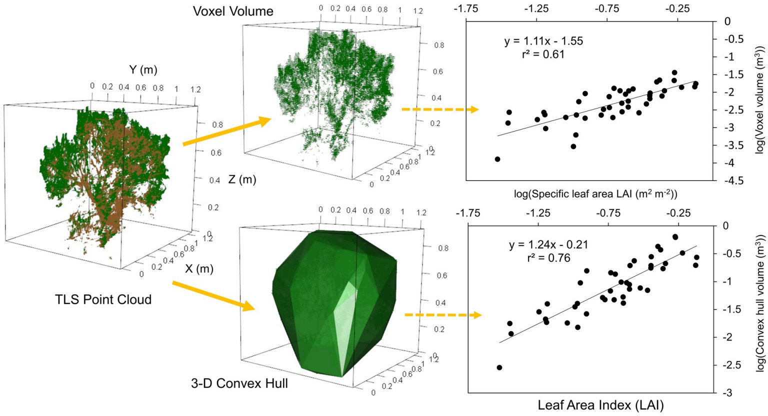

Voxel Volume
y = 1.11x - 1.55
r² = 0.61
log(Voxel volume (m³))
log(Specific leaf area LAI (m² m⁻²))
Y (m)
Z (m)
X (m)
TLS Point Cloud
3-D Convex Hull
y = 1.24x - 0.21
r² = 0.76
log(Convex hull volume (m³))
Leaf Area Index (LAI)