# LiDAR Measurement of Sagebrush Steppe Vegetation Heights

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## ABSTRACT

Small footprint LiDAR data were used to detect and characterize vegetation in a semi-arid sagebrush steppe environment in southeastern Idaho. Processing the raw data in individual flightlines maintained the high relative accuracy of the dataset and allowed for the detection of sub-meter vegetation. First return LiDAR pulse data were used to both determine the ground surface as well as calculate vegetation heights. Surface roughness maps based on vegetation heights were found to best capture the variability of the canopy and accurately distinguish burned and unburned areas. Field validation of a sagebrush presence and absence classification based on a single roughness threshold value indicate an overall accuracy of 86%. The LiDAR-determined vegetation heights are moderately well correlated to those measured in the field, though the LiDAR heights uniformly underestimate the field heights. This underestimation is believed to be due to signal threshold limits within the LiDAR sensor, producing heights corresponding to the interior of the shrub canopy rather than the top.

*Keywords:* remote sensing, vegetation, rangelands

## INTRODUCTION

Though a relatively young remote sensing technology, LiDAR (light detection and ranging, also referred to as laser altimetry or airborne laser swath mapping) has quickly demonstrated great potential to precisely characterize vegetative systems. Within forest canopies, both small (1 m or less) and large (10-25 m) diameter footprint LiDAR systems have found widespread success in the measurement of various ecological parameters. Waveform returns from large footprint LiDAR sensors such as the Scanning LiDAR Imager of Canopies by Echo Recovery (SLICER) and Laser Vegetation Imaging Sensor (LVIS) have successfully been used to measure variables such as tree height, canopy structure, leaf area index (LAI) and biomass (Drake et al., 2002; Harding et al., 2001; Hofton et al., 2002). Similarly, small footprint LiDAR data have been used to determine tree height and LAI in various forest types (Popescu et al., 2002; Riaño et al., 2004). Beneath the canopy, Seielstad and Queen (2003) have also used small footprint LiDAR data to measure fuel loads of coarse woody debris on the forest floor.

Despite the fact that rangelands make up an estimated 70% of the planet's land area (West, 1999), little work has addressed LiDAR applications in rangeland ecosystems relative to the large number of forestry studies. Height profiles created by profiling LiDAR sensors have been used to measure plant height and canopy cover in a rangeland environment (Weltz et al., 1994) as well as to model rangeland surface roughness (Ritchie et al., 1995). Other studies have demonstrated the applicability of scanning LiDAR combined with multispectral video imagery to map shrub coppice dunes in desert grasslands (Rango et al., 2000).

The purpose of this study is to investigate the utility of small footprint LiDAR for detecting and characterizing vegetation in a semi-arid sagebrush steppe. Sub-meter accuracies are currently achievable with LiDAR technology, allowing for the discrimination of short vegetation types. This study seeks primarily to determine the capability of LiDAR to detect the presence of sagebrush and other types of low shrub. Upon positive detection, the ability to quantify various ecological variables such as shrub height and ground cover is explored. The methods described here are similar to those used in Glenn et al. (2006) and Mundt et al. (2006), but are presented in more detail and with attention to validation, both qualitative and quantitative.

Sagebrush (*Artemisia tridentata*) is one of the most dominant species of vegetation in the intermountain West, with sagebrush communities present in all 11 western states (Bunting et al., 1987). Many vertebrate species utilize habitats within sagebrush steppe ecosystems to maintain viable populations, such as pygmy rabbit *(Brachylagus idahoensis)*, sage grouse *(Centrocercus urophasianus),* and sharptailed grouse *(Tympanuchus phasianellus)*. However, due to pressures from invasive species, grazing practices, agriculture, and altered fire regimes, sagebrush populations have been in decline throughout the last century. An estimated 3 million acres of public lands in the intermountain West have become dominated by invasive grasses such as cheatgrass (*Bromus tectorum*) or medusahead (*Taeniatherum caput-medusae*) (West, 1999), while big sagebrush in the Upper Snake subbasin alone has decreased an estimated 42% from historic levels (NPCC, 2004). In many areas, there has been a complete loss of the sagebrush ecosystem (Knick, 1999).

As sagebrush communities in the intermountain West become increasingly fragmented or disturbed due to agricultural and urban growth, range fires, and invasive weeds, critical habitats and historic grazing/browsing regimes become threatened (NPCC, 2004). For instance, sagebrush communities can require 15 years or more to return to preburn conditions following a fire (Bunting et al., 1987; Humphrey, 1984). Many sagebrush communities have a long history of disturbance (Knick and Rotenberry, 1997) and require active restoration techniques (Hemstrom et al., 2002; McIver and Starr, 2001). As a result, land managers and conservation agencies are in need of accurate tools to inventory and assess sagebrush ecosystems.

As in the case of forest canopies, LiDAR has the capability to provide information about rangeland vegetation structure such as heights, densities, and biomass, properties which may not readily be determined through the use of passive remote sensing. A study by Mundt et al. (2006) has shown that LiDAR can be used successfully to improve upon a hyperspectral classification of sagebrush presence/absence in southern Idaho. This study aims to demonstrate the potential of LiDAR to be a powerful and complementary tool in monitoring rangelands, both in pristine condition or after a disturbance.

### STUDY AREA

The study area for this investigation is located within the United States Sheep Experiment Station (USSES), a facility of the United States Department of Agriculture (USDA) Agricultural Research Service (ARS). This facility is located near Dubois, Idaho, in the northeastern Snake River Plain. The study area itself is located in the northeast corner of the USSES and is approximately 5 km long and 1 km wide, with a total area of 6.9 km2 (Figure 1). The terrain of the study area is gently rolling rangeland, with elevations between 1777 and 1866 m.

The dominant vegetation within the study area is mountain sagebrush (*Artemisia tridentata ssp. vaseyana*), while secondary shrub types include green rabbitbrush (*Chrysothamnus viscidiflorus*) and horsebrush (*Tetradymia canescens*). The average height of these shrubs within the study area is generally no more than one meter. Grasses and forbs include thickspike wheatgrass (*Elymus lanceolatus spp. lanceolatus*), Plains reedgrass (*Calamagrostis montanensis*), Idaho fescue (*Festuca idahoensis*), and bushy bird’s beak (*Cordylanthus ramosus*). Two controlled fires have occurred within the study area in recent years, both of which are indicated in Figure 1. The latter was in the northern part of the study area and took place in the fall of 2002, just prior to the acquisition of the LiDAR data. The earlier burn occurred in the eastern part of the study area in 1995. In areas where the fires were more intense, the sagebrush stems were burned completely to the ground, while in less intensely burned areas remnants of shrub stems and branches remain. The ecosystem within the 1995 burn is still recovering, albeit quite slowly. Seven years later, at the time of the data collection, the area was yet dominated by bare ground and grasses, with some sparse low brush.

This study area was selected for two principal reasons. The first is that the terrain has mild topography, making it amenable to vegetation discrimination without the complexities of rugged terrain. The second reason is that the burned areas provide a bare, non-vegetated state with which to compare and contrast the results from the vegetated areas.

## METHODS

### DATA CHARACTERISTICS AND ACCURACY

The LiDAR data were acquired in the fall of 2002 by the Airborne 1 Corporation of El Segundo, California, using an Optech ALTM 2025 LiDAR System. The sensor, which acquires data at a rate of 25 kHz, was mounted on a fixed wing aircraft flying with a minimum airspeed of approximately 100 kt. Both first and last pulse datasets were acquired, each consisting of over eight million individual postings having an average separation of 0.9 m (producing a post density of 1.2 m-2). The data were collected in nine separate flightlines, each approximately 300 m wide, resulting in flightline overlap of roughly 50%. All flightlines were then combined to form the final datasets. Each data point includes a Global Positioning System (GPS) time stamp and intensity value, as well as the spatial coordinates in three dimensions. The data were collected from an altitude of approximately 750 m, resulting in a footprint diameter of roughly 20 cm for each laser pulse.

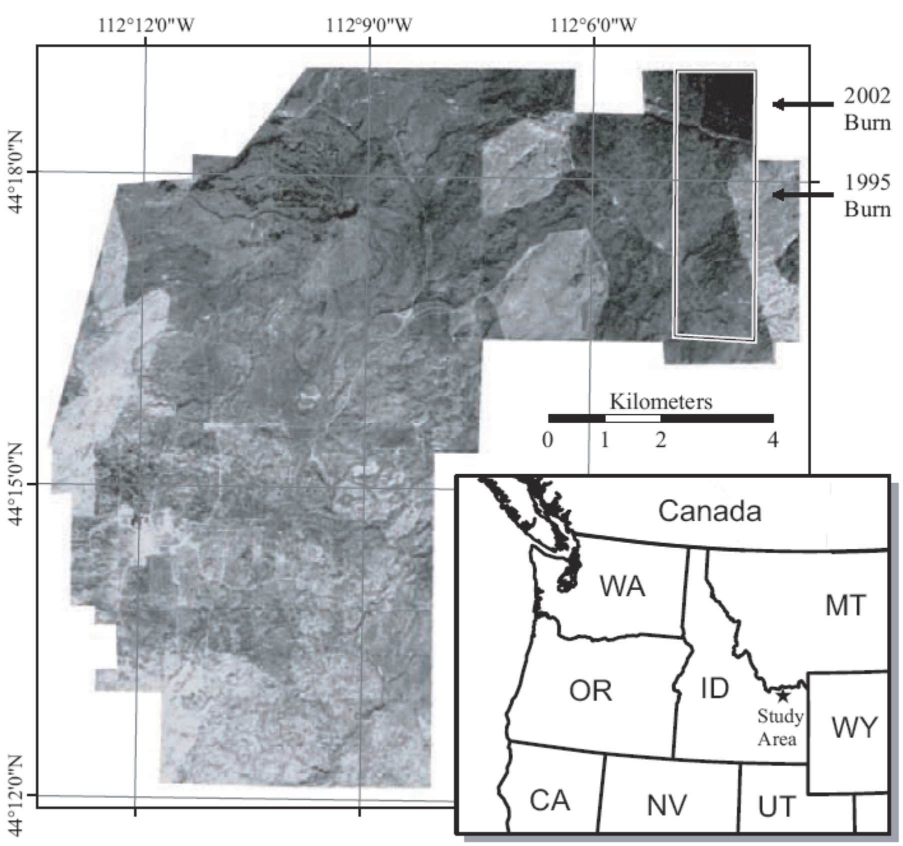


**Figure 1. A figure of the study area, outlined within the United States Sheep Experiment Station. The base map is a QuickBird image, acquired in October of 2002. The two burns within the study area are identified. The inset shows the location of the study area (as a star) within the state of Idaho.**

Once the LiDAR data were collected, both the absolute and relative accuracies of the dataset were determined. The absolute accuracy of LiDAR data determines how accurate the individual coordinates of each point are with respect to an absolute coordinate system or datum. Relative accuracy, on the other hand, determines how accurately individual points are located with respect to each other and provides a measure of the internal consistency within the dataset.

The vendor performed a GPS validation survey concurrent to the LiDAR acquisition and was able to constrain the absolute accuracy of the LiDAR coordinates to 22 cm in the vertical direction and 1 m in the horizontal direction (two-sigma; ASPRS, 2004). A comparable vertical accuracy was also determined using assessment methods modeled after Latypov (2002), which calculate the error between individual flightlines in areas of overlap.

One of the simplest ways to measure relative error is by performing a statistical analysis of a collection of points returned from a flat surface. Such surfaces may include a standing body of water, a flat and nonvegetated area of ground (e.g. a dry lakebed or parking lot), or the wall or roof of a building. LiDAR points that are returned from these surfaces are expected to lie on a flat plane, and thus any deviation away from a flat plane provides a measure of the relative accuracy (vertical accuracy in the case of bodies of water and rooftops, horizontal accuracy in the case of building walls).

Analyses in previous studies using LiDAR data collected on the same campaign as this study, though in different areas of southern Idaho, determined vertical and horizontal relative accuracies of 5 cm and 10 cm, respectively (Glenn et al., 2006; Mundt et al., 2006). As this study area contains no buildings or standing bodies of water, the vertical relative accuracy was estimated using flat areas of bare ground. Even if these bare areas contain minor topographic variability, they can still serve to determine an upper bound of the relative accuracy. Within the study area, numerous separate bare ground locations were distributed among multiple flightlines, each of which contained at least 50 LiDAR points with standard deviation of 5 cm or less. Relative accuracies of this magnitude can be expected when using a properly calibrated LiDAR sensor under normal operating conditions (Airborne 1, 2001). Figure 2 shows a histogram of the standard deviation of elevation over the entire study area, based on 25 m2 parcels. As can be seen from the shaded portion of the figure, several thousand such locations exist with standard deviation of 5 cm or less, indicating that the vertical accuracy of the sensor is within this limit.

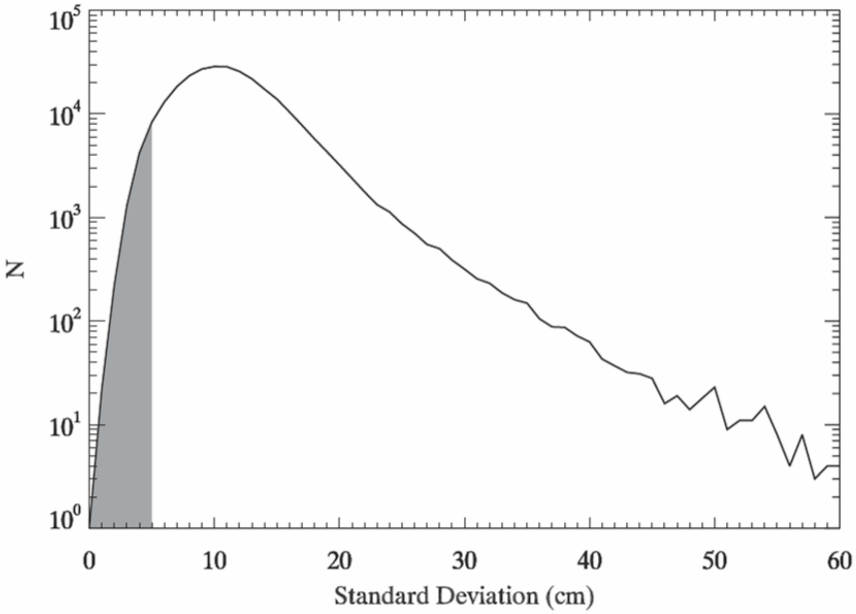


**Figure 2. A histogram of standard deviations of elevation over 25 m2 parcels for the entire study area. The shaded portion represents those areas with a standard deviation of 5 cm or less.**

Fifty-two ground control points (GCPs) were collected throughout the study area, primarily at road intersections and other easily identifiable features, with the use of a differentially-correctable Trimble GeoXT GPS unit. Due to the high vertical accuracy of the data, in combination with the available intensity data, many of these features were identifiable within the LiDAR dataset. Thus the GCPs were used to geometrically register the LiDAR dataset (which involved a datum conversion) and resulted in an RMS error of 0.75 m. The dataset was registered as a whole, without separating the individual flightlines. The calculated registration error is in general agreement with the absolute horizontal accuracy quoted by the vendor.

Initial field investigation of the study area found that the canopy cover was generally low throughout the site, exposing a large amount of bare ground. Because of this, in addition to the fact that the study area is relatively devoid of major topographic features, the first return LiDAR data were used to characterize both the terrain and the vegetative canopy. Using a single-return LiDAR dataset instead of attempting to merge the first and last return data kept the overall processing requirements to a minimum and, more importantly, avoided the introduction of problems associated with detecting multiple pulse returns at a similar height (Hodgson et al., 2003).

As stated earlier, the study area was chosen for this investigation in part because of its gentle topography, which would in turn aid in the extraction of vegetation heights from the LiDAR data. Figure 3 shows a semivariogram of the elevation data at lag distances up to 500 m. One can see from the figure that the semivariogram is parabolic near the origin, indicative of a Gaussian model of semivariance and characteristic of extremely continuous terrain (Isaaks and Srivastava, 1989). This result supported the premise that the ground could be modeled as a smooth and continuous surface.

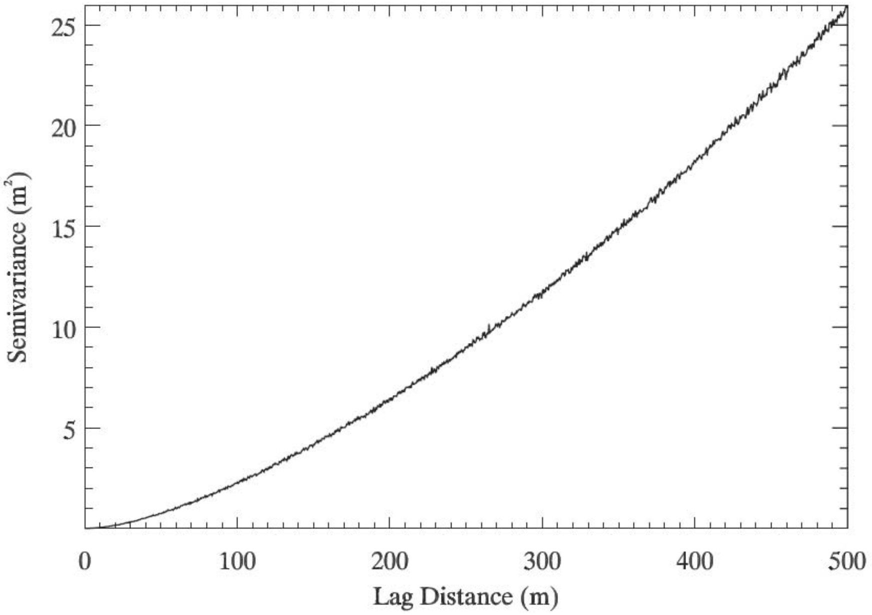


**Figure 3. A semivariogram of elevation heights for the study area.**

## HEIGHT CALCULATION

The LiDAR data were divided into 5 m × 5 m grid cells, each of which contained between 5 and 50 individual LiDAR points, depending on the local point density. Even though only the first return data were used in this study, it was assumed that, due to the open canopy, some fraction of the returned pulses were reflected entirely from the ground, without encountering any canopy cover. As such, the lowest point within each cell was assumed to have fully penetrated the canopy and been returned from the ground surface. With the use of these initial ground points, spaced an average of 5 m apart, a preliminary ground surface was interpolated across the entire study area using a thin plate spline (Meinguet, 1979). Due to local terrain irregularities, some low points, though not the absolute lowest in each cell, were as a result located below the initially interpolated ground surface. Points that lay on or below the ground surface were therefore reclassified as additional ground points. A new ground surface was then re-interpolated using the increased collection of ground points. This process was iterated until all LiDAR points were classified as either ground or non-ground. Ninety-eight percent of the points converged after two iterations of this procedure. All resulting ground points were used to interpolate a final ground surface, and heights above this surface were calculated for all remaining non-ground points.

Initial investigations determined that regions of poor relative vertical accuracy (25 cm or more) existed in many areas due to the overlap of multiple flightlines. Because this inaccuracy was greater than the majority of vegetation heights, the vegetation component was obscured and computed vegetation heights were inaccurate. However, when the methodology described above was applied to each of the flightlines individually instead of to the dataset as a whole, the relative accuracy increased considerably across all flightlines to the 5 cm level that was desired. In order to preserve the highest possible accuracy, the processing of vegetation heights was performed by considering all flightlines individually. Upon calculation of heights within each flightline, all flightlines were recombined into a single dataset.

As noted previously, the LiDAR dataset has a point density of 1.2 m-2 and a footprint diameter of approximately 20 cm. This results in the sampling of less than 10% of the actual surface throughout the entire region. In this way LiDAR can only be considered as a sampling method, providing a statistical measure of the surface topography. In terms of vegetation, only a small fraction of all plants are therefore sampled. This led to the consideration of statistical products to quantify the topography and any derived properties, such as vegetation heights or ground cover.

### RASTERIZATION

The point data were used to produce maps of various ecological properties, primarily mean height and surface roughness. This was done by dividing all of the point data into 5 m grid cells and statistically analyzing the data within each cell. The mean height was computed as the mean of all individual height values within the cell, while the surface roughness value was determined by calculating the standard deviation of the heights. Both products included the zero-height ground points so as to be characteristic of the data in entirety. Several other products were similarly calculated, such as the mean vegetation height (which excluded ground points) and tallest height within each cell. The percentage of vegetative cover was also calculated as the ratio of the number of non-ground points to the total number of points within each cell.

### VALIDATION

A validation campaign was carried out in the fall of 2004. One hundred and sixty-eight validation points were collected throughout the study area with a GPS unit. Each validation point consisted of the type of ground cover at that location (sagebrush, grass, burned remnants and litter, or bare ground) and the height of the vegetation, measured to the nearest 5 cm. When individual shrubs were measured, the maximum height of the shrub was recorded and the GPS point was centered on it. The field validation points also included an ocular estimate of the overall ground cover within a radius of 50 cm. These points were collected in three transects throughout the study area, one through an unburned area, one through the 1995 burn, and one through the 2002 burn. The number of validation points collected in each transect was roughly equal.

In order to investigate the relationship between the field and LiDAR measurements, the heights were compared using a spatial buffer. Due to the difficulty of precisely locating individual LiDAR points in the field, the field points were buffered horizontally when compared to the LiDAR point data. (A spatial buffer allows the absolute location of a point to vary within a specified radius.) The height of each sagebrush field point was compared to the highest individual LiDAR point within the buffered area, as the highest LiDAR point would most likely represent the shrub corresponding to the field measurement. Initially, the buffer size was varied in order to determine the optimal buffer radius. Based on 104 sagebrush points, it was found that the highest correlation between the field-measured heights and the LiDAR-calculated heights occurred at a buffer radius of approximately 1.5 m. (The analysis was restricted to sagebrush field points only, as bare ground field points would be unlikely to show significant spatial dependence.) Figure 4 shows the correlation coefficient (r) versus buffer size up to a buffer radius of 3.5 m. The correlation weakens for both larger and smaller radii, indicating that this buffer size was optimal for capturing isolated shrubs. The resulting buffer is large enough to accommodate horizontal inaccuracies and yet small enough to prevent confusion between multiple shrubs. Thus a buffer of 1.5 m was used throughout the remainder of the validation. It is interesting to note that the optimal buffer size is roughly equal to the sum of the horizontal LiDAR accuracy (calculated above) and the general accuracy of the GPS unit (<1 m).

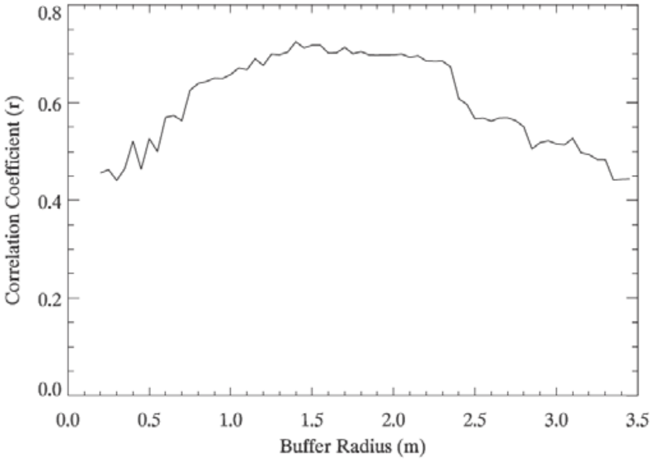


**Figure 4. A plot of correlation coefficient versus buffer size for all sagebrush field points.**

## RESULTS

An example cross-section of the resulting height data is shown in Figure 5. In the upper figure, the black line shows the first pulse LiDAR data and represents the top of the rangeland canopy. The grey line below it is the ground surface, calculated via the method explained above. In the lower figure, the ground elevations have been subtracted from the LiDAR data, resulting in the vegetation heights alone which are shown with the grey line. The black line represents the surface roughness, calculated as the standard deviation of the heights over 5 m intervals. As identified in the diagram, the cross-section intersects a boundary between burned and unburned areas. The burned side has correspondingly lower vegetation heights and surface roughness than the unburned side.

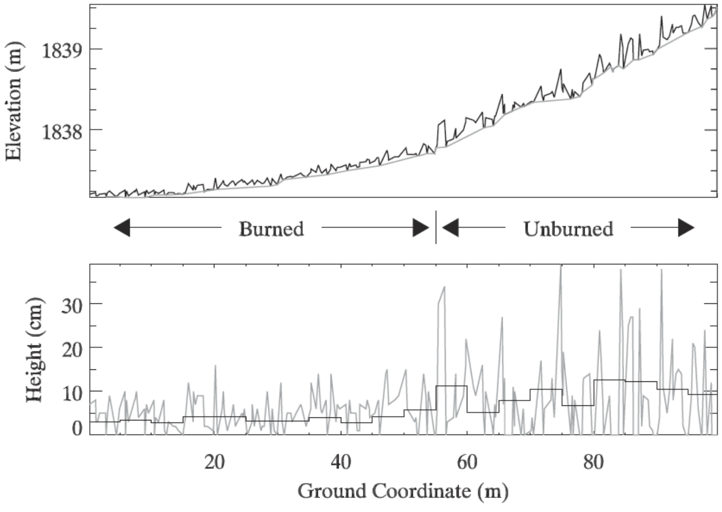


**Figure 5. A cross-section of the elevation data showing the individual vegetation heights above the ground surface. The upper figure shows the raw LiDAR points (black) above the interpolated ground surface (grey). The lower figure shows the corresponding individual vegetation heights (grey) and the surface roughness, calculated over 5 m intervals (black).**

VEGETATION HEIGHTS

Of the first pulse LiDAR points, 21% were classified as ground and the remainder as non-ground. Figure 6 shows images of the mean vegetation heights across the northern half of the study area, rasterized to 5 m pixels. Figure 6a shows the heights calculated from the entire dataset as a whole, while Figure 6b shows the heights calculated from the dataset after separating the flightlines. As shown in Figure 6a, the overlapping flightlines caused a north-south striped pattern of anomalous heights due to the degraded accuracy. These stripes disappear in Figure 6b, allowing the burned and unburned areas to be much more distinguishable and even revealing unimproved roads throughout the site. The height values calculated from the separated flightlines and represented in Figure 6b are used for the remainder of the analysis.

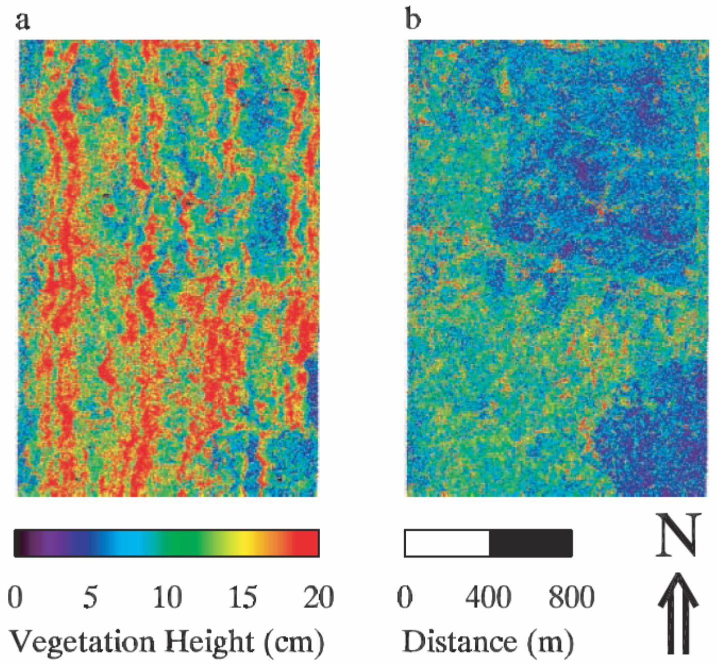


**Figure 6. Maps showing mean vegetation height rasters over a subset of the study area. a) The vegetation heights calculated from the combined dataset. b) The vegetation heights calculated from individual flightlines.**

Figure 7 is a histogram showing all individually calculated height values throughout the study area. The calculated non-ground heights range from 1 cm to 343 cm (likely a tree) and have a mean of 12 cm, a median of 9 cm, and a mode of 5 cm. Ten percent of the height measurements are equal to or greater than 25 cm, while the tallest 1% are equal to or greater than 45 cm. Within the sage dominated areas, the mean vegetation height is 13 cm. The mean heights in the 1995 and 2002 burns are 8 cm and 9 cm, respectively.

The histograms in Figure 8 compare the vegetation heights from the burned and unburned areas. In the figure, the solid line represents the unburned area, while the dotted line represents the 1995 burn and the dashed line represents the 2002 burn. As expected, the vegetation heights are greater in the unburned area than in the burned areas. Table 1 shows the statistical properties of the heights within each subset. (The vegetative fraction listed in the table is calculated as the ratio of non-ground points to the total number of points throughout the entire subset.)

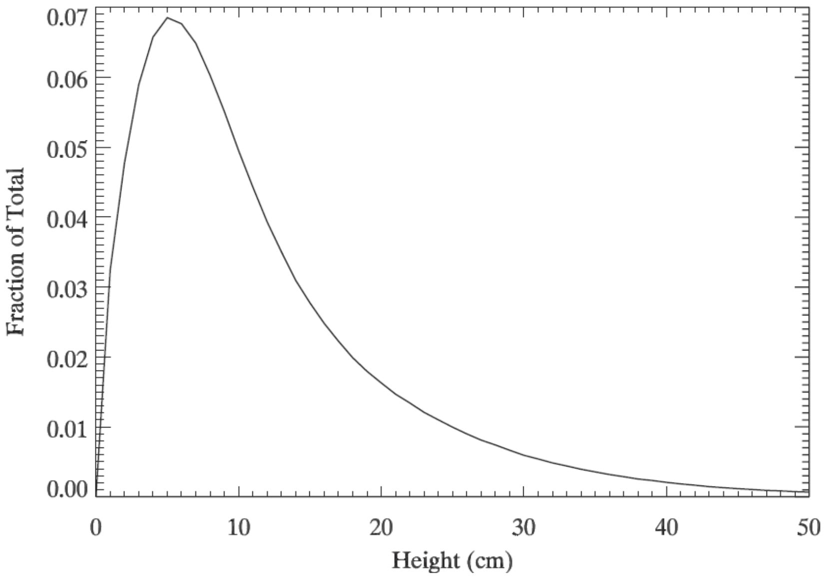


**Figure 7. A histogram of individual vegetation heights for the entire study area.**

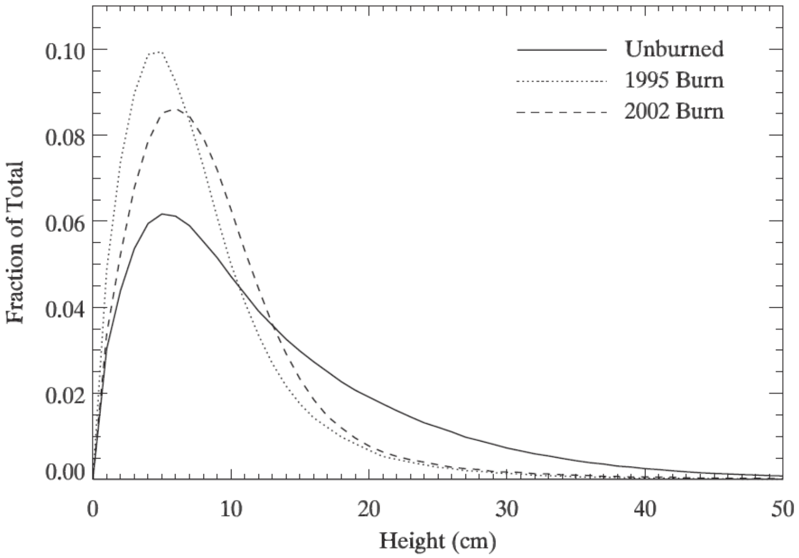


**Figure 8. A histogram comparing the vegetation heights of burned and unburned areas.**

Table 1. Vegetation height statistics for the burned and unburned areas.

| Area | Mean Height (cm) | Median Height (cm) | Standard Deviation (cm) | Height of 95th Percentile (cm) | Vegetation Fraction |
|---|---|---|---|---|---|
| Unburned | 13 | 10 | 10 | 33 | 0.801 |
| 1995 Burn | 8 | 6 | 6 | 19 | 0.766 |
| 2002 Burn | 9 | 8 | 7 | 20 | 0.765 |

<u>SURFACE ROUGHNESS</u>

Due to the irregular and open nature of the sagebrush canopy, surface roughness, calculated as the standard deviation of the vegetation heights, was found to better capture the variability of the canopy than other statistical measures, such as mean height or skewness. The calculated surface roughness values ranged from near zero to 2.5 m. Unburned, sage dominated areas have a mean surface roughness value of 10 cm, while both of the burned areas have a lower surface roughness mean of 5 cm. Figure 9 shows a histogram of surface roughness for both burns as well as an unburned region. Unlike the vegetation heights, the histograms of surface roughness demonstrate high separability of the burned areas from the unburned area, as evidenced by the two distinct peaks. From the figure, we see that the burned and unburned areas may be separable using a threshold value near 6 cm, where the burned and unburned histograms intersect. Table 2 shows the statistical properties of each subset calculated from the rasterized maps.

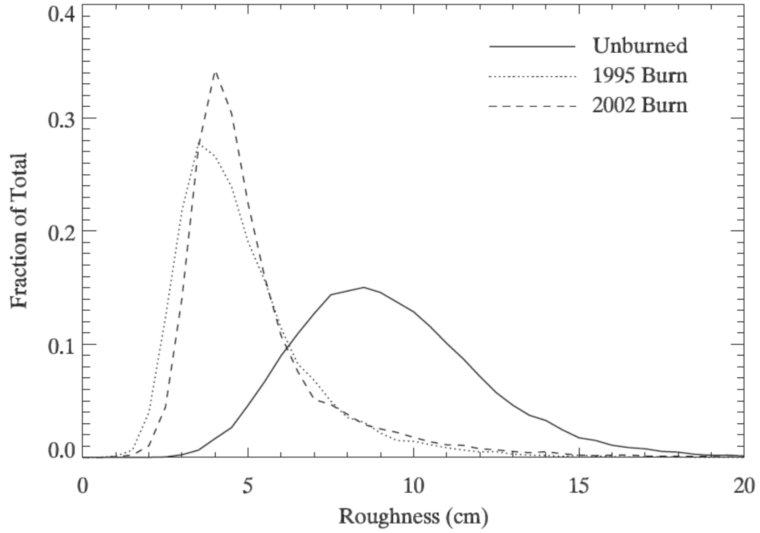
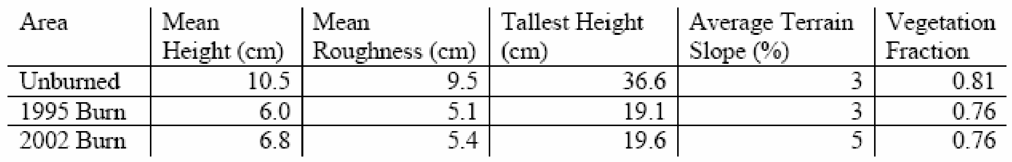


**Figure 9. A histogram comparing the surface roughness of burned and unburned areas.**

Table 2. Vegetation statistics after rasterization for the burned and unburned areas.



| Area | Mean Height (cm) | Mean Roughness (cm) | Tallest Height (cm) | Average Terrain Slope (%) | Vegetation Fraction |
|---|---|---|---|---|---|
| Unburned | 10.5 | 9.5 | 36.6 | 3 | 0.81 |
| 1995 Burn | 6.0 | 5.1 | 19.1 | 3 | 0.76 |
| 2002 Burn | 6.8 | 5.4 | 19.6 | 5 | 0.76 |

Figure 10 compares the map of surface roughness to a multispectral image (pan-sharpened QuickBird, acquired within weeks of the LiDAR data) of the northern half of the study area. The contrast of the burned to unburned areas is quite visible in the surface roughness map, with clear boundaries between the two regions. Nearly all of the burned areas from both the 1995 and 2002 fires are clearly visible in the map of surface roughness. In comparison to the map of mean height in Figure 6b, the map of surface roughness appears to better demonstrate changes in overall landcover.

## VALIDATION

Of the 168 validation points collected in the field, 104 were classified as sage, 5 as grass, 4 as rock, 13 as bare ground, and 42 as burned remnants. The first validation test was simply a presence/absence accuracy assessment for sagebrush, following the method of Congalton and Green (1999). The classification is based on the surface roughness calculation, using a simple threshold value for presence and absence. (Roughness values greater than the threshold indicate sagebrush presence, while values less than the threshold indicate absence.) Sagebrush presence was based on direct field observation, while points categorized as bare ground, rock, or grass in the field were classified as sagebrush absence. (Burned remnants were excluded from the analysis as no distinction was made in the field between remnants that remained standing and remnants that had burned almost entirely to the ground.) The error matrix in Table 3 shows the bivariate frequency distribution for sagebrush presence and absence using a threshold value of 5 cm, which produced the highest accuracies. As can be seen from the table, the 5 cm threshold classifies the sagebrush presence quite well, to Producer's and User accuracies of 88% and 94%, respectively. While the Producer's accuracy of sagebrush absence is also reasonably high at 74%, the User accuracy of sagebrush absence is a relatively poor 57%. This indicates confusion between sagebrush present in the field and points classified as absent in the LiDAR classification. The overall accuracy of the classification is 86%.

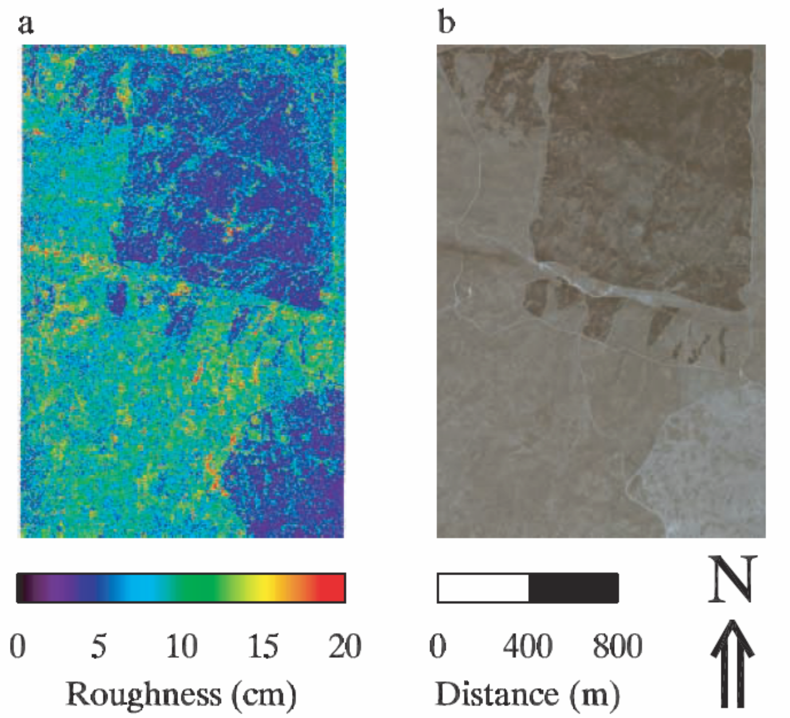


**Figure 10. A comparison of a) a map of the calculated surface roughness to b) a true-color QuickBird scene for the northern half of the study area.**

Table 3. Error matrix for the field validation of sagebrush presence and absence.

| | Field Present | Field Absent | Total | User Accuracy |
|---|---|---|---|---|
| LiDAR Present | 92 | 6 | 98 | 94% |
| LiDAR Absent | 12 | 16 | 28 | 57% |
| Total | 104 | 22 | 126 | |
| Producer's Accuracy | 88% | 72% | | 86% (Overall) |

The field-measured heights were then compared directly to the individual LiDAR-calculated heights, as well as to the local surface roughness. The comparison of field-measured and LiDAR-calculated heights resulted in a correlation coefficient of $r = 0.64$. When the comparison is restricted to field measurements of sagebrush only, the correlation increases to 0.72. Figure 11 shows a scatterplot of the LiDAR-derived heights versus field heights for all of the field measurements. Though the correlation is weak, a test of correlation shows it to be significant at 99% confidence (Davis, 1986). The correlation between field height and LiDAR roughness values was similar, at 0.70. A linear regression analysis determines that Hfield = 1.5 × HLiDAR + 25 cm best describes the data. The dashed line in Figure 11 represents this regression, while the dotted line signifies an ideal 1:1 association.

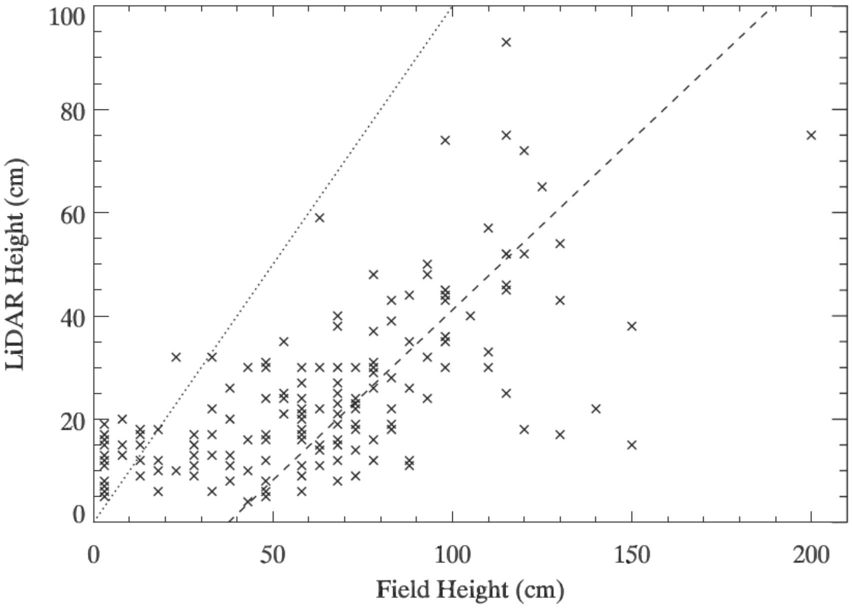


**Figure 11. A comparison of individual field-measured height values versus LiDAR-determined height values. The dashed line is a best-fit linear regression to the data, while the dotted line represents a 1:1 correspondence.**

## DISCUSSION

Regardless of the methods used to generate or compare them, the LiDAR heights are consistently lower than the field measurements. Most sources of error, such as in field survey methods or due to sensor inaccuracies, are stochastic and would not contribute to an overall reduction in the LiDAR heights. The LiDAR heights, on the other hand, appear to be systematically lower than the field measurements in almost all areas. When a linear regression is performed on the LiDAR and field heights, the LiDAR heights are found to be approximately half as high as the field heights, as shown in Figure 11. This could be due to the inherent properties of the LiDAR scanner or the method by which the heights are determined from the LiDAR data. Also apparent in the figure is the lack of correlation between LiDAR and field heights below approximately 20 cm. It may be that this represents an operational lower limit for height determination.

Due to the two-year interval between acquisition of the LiDAR data and the collection of field points, some growth may have occurred affecting the accuracy of the validation. These effects could vary depending on which regions of the study area are in question: the 2002 burn, the 1995 burn, or the unburned area. Within the 2002 burn, all recent vegetation (generally consisting of grasses) was ignored and only burned remnants were measured. These remnants are assumed to be unchanged over the two year interval, and thus should not be a source of error. It was also assumed, based in part on field observation, that only minor canopy changes occurred within the 1995 burn or unburned areas. Independent test plot measurements indicate that sagebrush canopy varies by roughly 10% over a two-year interval (Inouye, private communication), equivalent to approximately 10 cm in the context of this study. While this may contribute to the overall underestimation of heights by LiDAR, it would represent only a minor component of the discrepancy.

Overall, the sagebrush presence/absence classification based on surface roughness performed well. However, the User accuracy of sagebrush absence was a rather poor 57%, indicating that a significant amount of sagebrush was not detected by the LiDAR analysis. In fact, the average field-measured height of the sagebrush at these locations was 54 cm, implying that the LiDAR data simply missed these shrubs. This is not altogether surprising, considering that the width of the shrubs themselves is on the order of 1 m, roughly the same as the absolute horizontal accuracy of the LiDAR data.

This reflects the most difficult step in this study, which was trying to compare LiDAR data points, having a footprint diameter of approximately 20 cm, with ground truth data that has been co-registered to 0.75 m, an inaccuracy several times the width of the footprint. As a result, it was not possible within the scope of the study to determine the exact location of each LiDAR footprint on the ground, but only to within one meter or so. It was therefore necessary to buffer the data, introducing a significant uncertainty. One consequence of this is the likelihood that a large number of the LiDAR pulses were reflected not from the top of the canopy, but instead from the shoulders of the individual shrubs. This is most certainly the case in some portion of the measurements, and would indeed serve to decrease many of the calculated heights. However, it must then also be concluded that some fraction of the pulses were reflected from the top of the crowns and, barring other sources of error, should produce accurate heights. Yet, as shown in Figure 11, this appears not to be the case. In fact, if the shorter, uncorrelated points are excluded, the vast majority of the remaining points lie well below the 1:1 line.

This in turn leads to the question of whether or not the LiDAR pulse penetrates some distance into the canopy before it is reflected. Unfortunately, the current literature does not discuss the minimum detection threshold for common LiDAR sensors. The low LiDAR heights calculated in this study seem to indicate the possibility that the pulse does not reflect sufficiently from the absolute top of the vegetation, but does in fact penetrate into the canopy to some extent before a detectable reflection occurs. Therefore the LiDAR calculated heights would be systematically lower than the field measured heights, necessitating an approximation such as incorporating a scale factor and/or a correction constant into the height derivation. Such a correction would likely be vegetation specific, depending on the overall density of the target. In the case of sagebrush, this scale factor appears to be between 1.5 and 2.0. A scale factor may also accommodate other types of inaccuracies, such as that due to reflections from shrub shoulders discussed above.

The local canopy coverage does seem to play a role in how well the LiDAR measures the vegetation structure. As stated previously, the correlation between field measured height and LiDAR measured height is 0.64, while the correlation between field measured height and LiDAR measured roughness is 0.70. However, when restricted to validation points where the canopy coverage is 50% or more (49 points, as determined by field observations), these correlations increase to 0.78 and 0.79, respectively.

Although the accuracies of the classification increase with canopy cover, too dense of a canopy would likely lower the accuracies. As stated earlier, the last pulse data were not used in this study for the principle reason that current LiDAR systems do not seem to be able to discriminate multiple returns from similar heights, due to signal detection threshold and timing limits within the LiDAR sensor, the vertical width of the individual laser pulses, and inaccuracies in co-registering multiple returns both vertically and horizontally. As such, it was necessary to use the first pulse data to characterize both the rangeland canopy and the ground surface. One of the limitations of this methodology is that it is appropriate only for an open canopy. If the canopy is too dense, to the point of preventing a sufficient number of ground returns with which to generate an accurate ground surface, then this methodology would be unlikely to produce accurate results. There would also be a balance between maximum canopy cover and terrain variability. The terrain of this study area in this investigation is relatively gentle, and therefore requires fewer ground points for an accurate interpolation. A more rugged and variable terrain would require more ground points and therefore a more open canopy.

Although the vegetation heights within the two burned areas are quite similar, the heights within the more recent 2002 burn are, paradoxically, slightly higher than within the older 1995 burn. The difference is so small as to be below the accuracy of the study, though the heights within the 1995 burn would be expected to be higher. It is not known why this difference exists, though possible explanations include the poor recovery of the ecosystem within the 1995 burn, differences in burn severity between the two burns, the seeming inability of the LiDAR algorithms to detect very low height brush and grass, or some combination of these factors. As noted in Table 2, the area of the 2002 burn has a slightly higher average slope than that of the 1995 burn, which also may have influenced the LiDAR height determination.

It is probable that the methods used to estimate vegetation fraction (the results of which are shown in Tables 1 and 2) overestimated the overall vegetation cover. This is not unexpected, however, in that it was calculated as simply a ratio of vegetation returns to the total number of returns. The ground returns, by definition, are assumed to contain no vegetation within their footprint. The non-ground returns, on the other hand, need only contain a minimal amount of vegetation to provide detection. This produces a bias toward non-ground points, effectively oversampling the vegetation cover.

It is also uncertain as to whether or not this methodology can detect or characterize rangeland grasses. The study area was relatively lacking in grassy areas, with only five validation points classified as such in the field. Due to the problem detecting low sagebrush and the uncertainty regarding pulse return threshold limits discussed above, it is questionable whether the current methodology would be able to distinguish grass from bare ground.

## CONCLUSIONS

This study showed that LiDAR data can be successfully used to detect and characterize vegetation in a rangeland environment. However, relative vertical accuracies on the order of 5 cm are required to resolve low vegetation heights and care was needed in order to preserve this accuracy throughout the study. As such, all data were processed and heights calculated in raw point format, without rasterization. This also required the processing of all data in individual flightlines, and recombining into a single dataset only at the time of analysis.

In a sagebrush dominated area, the mean LiDAR-derived vegetation height was found to be 12 cm, while the individual vegetation heights ranged as high as 343 cm. Surface roughness calculations were found to be a useful measure of surface variability within this ecosystem and better distinguished ecological regimes than other types of statistical measure. Burned and unburned areas were found to be easily identifiable using LiDAR-determined height measurements and statistical analysis. A roughness value of 5 cm was found to classify sagebrush presence and absence to an overall accuracy of 86%.

While LiDAR data have been used a great deal in the study of forest ecosystems, this study shows that they can also be of significant use in rangelands or other low-canopy regions. Possible uses include biomass and fuel load estimation, determining burn severity and rates of recovery following disturbance, and habitat characterization, such as the identification of sage grouse leks (large areas of bare ground used for display and courting). The success shown in classifying sagebrush presence and absence indicates that this methodology may be of use in determining burn boundaries, even if a significant amount of time passes between the burn and the data acquisition. There is also the potential for possible inclusion into ongoing ecological studies at the station, such as evaluating the impact of various sheep grazing practices on sagebrush health (Bork et al., 1998; Seefeldt and McCoy, 2003). However, further investigations are necessary to better estimate actual sagebrush heights and densities from LiDAR measurements. The applicability of these methods in more rugged terrain or denser canopy must also be addressed, as well as the possibility of including data containing multiple returns.

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## LITERATURE CITED

Airborne 1 (2001). LiDAR accuracy. *Briefing Note BN#01*, Airborne 1 Corporation, El Segundo, California, 24 pp.

ASPRS (2004). Guidelines - vertical accuracy reporting for lidar data. *1.0*, American Society for Photogrammetry and Remote Sensing, Bethesda, Maryland, 15 pp.

Bork, E. W., West, N. E., & Walker, J. W. (1998). Cover components on long-term seasonal sheep grazing treatments in three-tip sagebrush steppe. *Journal of Range Management*, *51*, 293-300.

Bunting, S. C., Kilgore, B. M., & Bushey, C. L. (1987). Guidelines for prescribed burning sagebrush-grass rangelands in the northern Great Basin. *General Technical Report INT-231*, Intermountain Research Station, United States Department of Agriculture Forest Service

Congalton, R. G., & Green, K. (1999). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. Boca Raton, Florida: CRC Press 137 pp.

Davis, J. C. (1986). *Statistics and Data Analysis in Geology*. New York: John Wiley & Sons 646 pp.

Drake, J. B., Dubayah, R. O., Clark, D. B., Knox, R. G., Blair, J. B., Hofton, M. A., Chazdon, R. L., Weishampel, J. F., & Prince, S. D. (2002). Estimation of tropical forest structural characteristics using large-footprint lidar. *Remote Sensing of Environment*, *79*, 305-319.

Glenn, N. F., Streutker, D. R., Chadwick, J., Thackray, G. D., & Dorsch, S. (2006). Analysis of LiDAR-derived topographic information for characterizing and differentiating landslide morphology and activity. *Geomorphology*, *73*, 131-148.

Harding, D. J., Lefsky, M. A., Parker, G. G., & Blair, J. B. (2001). Laser altimeter canopy height profiles: Methods and validation for closed-canopy, broadleaf forests. *Remote Sensing of Environment*, *76*, 283-297.

Hemstrom, M. A., Wisdom, M. J., Hann, W. J., Rowland, M. M., Wales, B. C., & Gravenmier, R. A. (2002). Sagebrush-steppe vegetation dynamics and restoration potential in the interior Columbia Basin, U.S.A. *Conservation Biology*, *16*, 1243-1255.

Hodgson, M. E., Jensen, J. R., Schmidt, L., Schill, S., & Davis, B. (2003). An evaluation of LIDAR- and IFSAR-derived digital elevation models in leaf-on conditions with USGS Level 1 and Level 2 DEMs. *Remote Sensing of Environment, 84*, 295-308.

Hofton, M. A., Rocchio, L. E., Blair, J. B., & Dubayah, R. (2002). Validation of Vegetation Canopy Lidar sub-canopy topography measurements for a dense tropical forest. *Journal of Geodynamics, 34*, 491-502.

Humphrey, L. D. (1984). Patterns and mechanisms of plant succession after fire on *Artemisia*-grass sites in southeastern Idaho. *Vegetatio*, *57*, 91-101.

Isaaks, E. H., & Srivastava, R. M. (1989). *Applied Geostatistics*. New York: Oxford University Press 561 pp.

Knick, S. T. (1999). Requiem for a sagebrush ecosystem? *Northwest Science*, *73*, 53-57.

Knick, S. T. and Rotenberry, J. T. (1997). Landscape characteristics of disturbed shrubsteppe habitats in southwestern Idaho (U.S.A.). *Landscape Ecology*, *12*, 287-297.

Latypov, D. (2002). Estimating relative LiDAR accuracy information from overlapping flight lines. *ISPRS Journal of Photogrammetry & Remote Sensing*, *56*, 236-245.

McIver, J. and Starr, L. (2001). Restoration of degraded lands in the interior Columbia River Basin: Passive vs. Active approaches. *Forest Ecology and Management*, *153*, 15-28.

Meinguet, J. (1979). Multivariate interpolation at arbitrary points made simple. *Journal of Applied Mathematics and Physics*, *30*, 292-304.

Mundt, J. T., Streutker, D. R., & Glenn, N. F. (2006). Mapping sagebrush distribution using fusion of hyperspectral and lidar classifications. *Photogrammetric Engineering & Remote Sensing*, *72*, 47-54.

NPCC (2004). Upper Snake subbasin assessment. Northwest Power and Conservation Council, Portland, Oregon, 75 pp.

Popescu, S. C., Wynne, R. H., and Nelson, R. F. (2002). Estimating plot-level tree heights with lidar: Local filtering with a canopy-height based variable window size. *Computers and Electronics in Agriculture, 37*, 71-95.

Rango, A., Chopping, M. J., Ritchie, J. C., Havstad, K., Kustas, W., & Schmugge, T. (2000). Morphological characteristics of shrub coppice dunes in desert grasslands of southern New Mexico derived from scanning LIDAR. *Remote Sensing of Environment, 76*, 26-44.

Riaño, D., Valladares, F., Condés, S., & Chuvieco, E. (2004). Estimation of leaf area index and covered ground from airborne laser scanner (lidar) in two contrasting forests. *Agricultural and Forest Meteorology*, *124*, 269-275.

Ritchie, J. C., Humes, K. S., & Weltz, M. A. (1995). Laser altimeter measurements at Walnut Gulch watershed, Arizona. *Journal of Soil and Water Conservation*, *50*, 440-442.

Seefeldt, S. S. and McCoy, S. D. (2003). Measuring plant diversity in the tall threetip sagebrush steppe: Influence of previous grazing management practices. *Environmental Management*, *32*, 234-245.

Seielstad, C. A. and Queen, L. P. (2003). Using airborne laser altimetry to determine fuel models for estimating fire behavior. *Journal of Forestry*, *101*, 10-15.

Weltz, M. A., Ritchie, J. C., & Fox, H. D. (1994). Comparison of laser and field measurements of vegetation height and canopy cover. *Water Resources Research*, *30*, 1311-1319.

West, N. E. (1999). Managing for biodiversity of rangelands. In W. W. Collins, & C. O. Qualset (Eds.), *Biodiversity in Agroecosystems* (pp. 101-126). Boca Raton, Florida: CRC Press