A Comparison of Accuracy and Cost of LiDAR versus Stand Exam Data for Landscape Management on the Malheur National Forest

Susan Hummel, A.T. Hudak, E.H. Uebler, M.J. Falkowski, and K.A. Megown

ABSTRACT

Foresters are increasingly interested in remote sensing data because they provide an overview of landscape conditions, which is impractical with field sample data alone. Light Detection and Ranging (LiDAR) provides exceptional spatial detail of forest structure, but difficulties in processing LiDAR data have limited their application beyond the research community. Another obstacle to operational use of LiDAR data has been the high cost of data collection. Our objectives in this study were to summarize, at the stand level, both LiDAR- and Landsat (satellite)-based predictions of some common structural and volume attributes and to compare the cost of obtaining such summaries with those obtained through traditional stand exams. We found that the accuracy and cost of a LiDAR-based inventory summarized at the stand level was comparable to traditional stand exams for structural attributes. However, the LiDAR data were able to provide information across a much larger area than the stand exams alone.

Keywords: silviculture, forest management, LiDAR, inventory, stand exams

Remotely sensed data are helping people understand the dimensions and distribution of trees in forested areas that are too large or rugged to survey on foot alone. This is a global trend that is helping document the status of forests worldwide. Because remotely sensed data are typically collected above the canopy, one persistent question is how well such data can be used to inform operational decisions in forestry. It is an important question because digital remote sensing data are now supplanting the aerial photo surveys that foresters used for decades. Landsat satellite imagery is inexpensive and has been useful at a regional scale, but lacks the higher spatial resolution preferred for local project decisions. Light Detection and Ranging (LiDAR) data are receiving more attention because of their detailed structural information and established accuracy in research studies (Eid et al. 2004, Næsset 2002, 2009). Progress in addressing the question about operational uses of LiDAR is being made for some local forest attributes (e.g., Hudak et al. 2008b, Hollaus et al. 2009, Falkowski et al. 2010). Information is still lacking, however, on how the different sources of remotely sensed data and the methods to process them into useable information compare with one another in terms of a gain in knowledge about forest conditions relative to their overall cost. To address this need, we evaluated how information derived from both Landsat satellite and LiDAR data compared, in terms of accuracy and cost, with data collected by using traditional field exams. We also considered how the physical size of a management area might impact the relationship.

Background

A historical focus on increasing timber yield via forest management contributed to early field methods for estimating tree growth at different levels of competition (Hummel and O'Hara 2008); measurements or observations of forest structure were typically made within small, homogeneous units, or stands. Today, however, wood fiber is just one of many resources considered by forest managers, who may be responsible for decisions impacting multiple resources over large, heterogeneous land-

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scapes comprising many forested and nonforested units. In such instances, the geographic scale and detail of the information required for management can differ across the various disciplines involved in forest planning. For example, silviculturists typically focus on stand structural attributes (e.g., volume per diameter class), whereas wildlife biologists might consider landscape patterns arising from among-stand forest structures such as snag density. There is a need for forest inventory tools that are scale appropriate by discipline but remain compatible when combined in forestwide planning efforts (e.g., National Environmental Policy Act). For this reason remotely sensed data are being coupled with prediction algorithms to extend plot-level forest inventory data across large areas (Hudak et al. 2008a, 2009a and b, Pierce et al. 2009).

Imputation is one method being used to extend forest plot data to landscapes. It is a procedure for filling in missing values with measured values (Eskelson et al. 2009). In the context of forest management, imputation is used to assign stand exam data from stands that were sampled on the ground to similar stands that were not. This is useful because forest managers can not afford to inventory all stands across the large landscapes they manage.

In Oregon, for example, personnel on the Malheur National Forest (Malheur NF) use an imputation program (Most Similar Neighbor) to assign forest structure and volume attributes measured in sample stands to unsampled, but similar stands (Moeur and Stage 1995), and then use the results for landscape-level planning. Their interest in understanding the strengths and limitations of traditional forest inventory versus LiDAR-derived forest inventory made this study possible.

We sought to determine if remotely sensed data—in combination with field plots—could be used to obtain information of similar quality and cost to traditional stand exams, but over an entire project area. Our test of this was whether LiDAR and satellite data made it possible to create a wall-to-wall forest inventory that was of equal or better quality than one generated by using traditional stand exam plot data for the same landscape. We defined quality not in terms of map resolution, but in terms of predicting forest structure and volume attributes with the same or better accuracy at the stand level. We also calculated how the per acre cost of inventory information generated from the remotely sensed data compared with the per acre cost of stand exam data at the same level of accuracy for specific forest inventory attributes.

As long as forests are managed stand by stand, evidence is needed to show that inventories based on remote sensing data are as accurate as exam-based inventories at this same scale. Hence, stands are the units sampled and evaluated in our study. We evaluated satellite remote sensing data in addition to LiDAR data and we compared the suitability of both parametric and nonparametric statistical tests for assessing the accuracy of remote sensing versus traditional inventory. In this article we focus on results from the LiDAR analysis.

Methods

Study Area

This study occurred on the Blue Mountain Ranger District of the Malheur NF in Oregon (Figure 1). Planning staff of the Malheur NF routinely evaluate conditions for all land located in priority subwatersheds. We focused on two of them, the Shirttail and Van Aspen subwatersheds, which together cover 40,957 ac. Of this total area, roughly one-half (19,781 ac) lies within the Malheur NF boundary and includes both federal (18,423 ac) and private (359 ac) land. Nonforest land is also present (Figure 1).

Two subunits of an existing planning project (nicknamed "Damon") within the selected subwatersheds were flown with LiDAR to delimit our study area. Both units are south of John Day, Oregon, and lie on opposite sides of the town of Seneca (latitude 44.14°, and longitude −118.97°). The northern unit of the Damon project covers 9,598 ac and the southern unit covers 22,016 ac (Figure 1). Using regional protocols, Malheur NF staff delineated the Damon project area into 1,029 stands in a geographic information system database. The average stand size was 19.2 ac (SD 27.47) for federal land and 9.9 (SD 9.9) for private land. The stands were not edge matched to the subwatershed boundaries; consequently, some tiny sliver cells (<1 ac) affect the minimum size and summary statistics.

Data Collection

Field Data. Forest inventory plot data were collected in the study area during August and September of 2007. Eighty-eight stands were selected for sampling. The following criteria were applied to select the 88 inventory stands: (1) 100% sample of minority stand conditions, including one juniper woodland and one ponderosa pine invasion (into sagebrush) stand, and (2) stratified sample allocated proportionally in three canopy closure categories (low <20%; medium 20–40%; and high >40%). Most forest types in this area are dry ponderosa pine or dry mixed-conifer. Canopy closure is rarely above 60%. Previous experience by Malheur NF within the lowest category (including difficulty distinguishing between plantations and seed tree cuts in aerial photos) suggested more intensive sampling in it compared with the medium and high categories. Samples were distributed across a range of aspect and elevation. The 88 sample stands covered about 5,280 ac and averaged 59 ac (SD 49.6). Field measurements were made as follows:

1. In each of the 88 sample stands, variable-radius plots were measured by following established US Forest Service protocols for stand exams (see US Forest Service 2009). The total number of plots (641) was determined by accepting a 20% error for basal area (BA) estimates at a 66% confidence level. A BA factor was selected so four to eight trees were measured per plot. Plots were spaced to have roughly 1 plot/8 ac, although they could be closer together in stands with smaller overall area to accommodate a minimum of 3 plots/stand and a maximum of 15 plots/stand. Once the tree data were tallied, stand summaries were generated by using the Forest Vegetation Simulator (Dixon 2002) Blue Mountain variant. In this study, the variable-radius stand exams are used as validation data to test the accuracy of the imputation algorithm.
2. In each of the 88 sample stands, a fixed-radius plot (1⁄10 ac) was installed at one randomly selected variable-radius plot location. All trees of ≥5-in. dbh within the fixed area plot were measured. A Trimble GeoXT global positioning systems (GPS) unit was used to record the center point of every inventory plot (both variable- and fixed-radius plots). In this study, the fixed-radius plots are used as training data in the imputation algorithm.

Costs of Field Data Acquisition. The price per plot to acquire the variable-radius stand exam data in the Damon study was $17.34. This price, which ranges from $17 to 23 on similar sites depending on slope, road access, and species mixtures, could be as

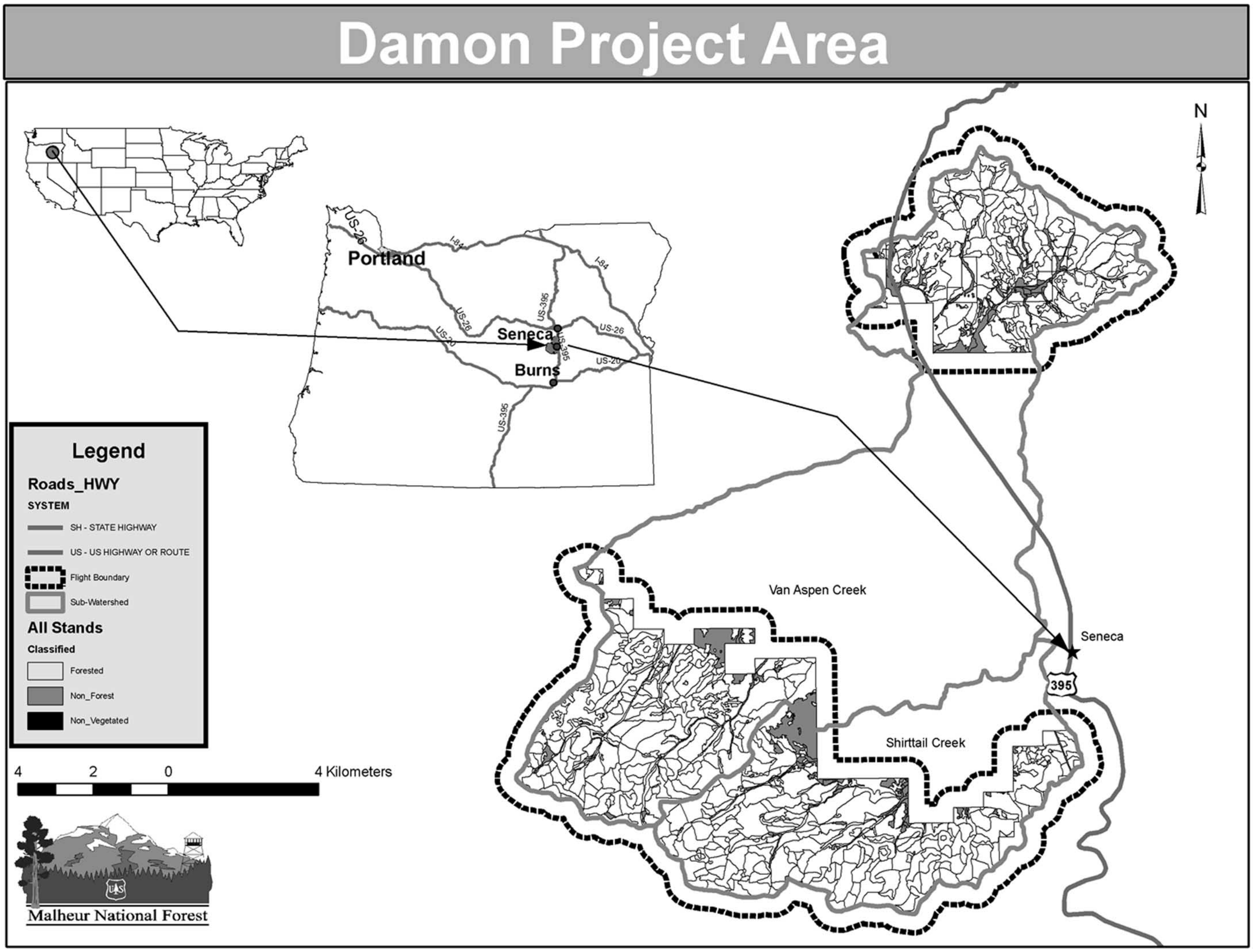

Figure 1. Damon project area, Malheur NF in Oregon.

high as \$32–42/plot if measurements of tree age, growth, or down wood are made.

The price per plot to acquire the fixed-radius plot data was \$57; however, this cost is considered low because of contract efficiencies gained by coupling the measurement of the fixed-radius plots with the same field visit as the variable-radius plots. If, as is more likely, the two types of field measurements are not done concurrently, but independently, we estimate the price for fixed-radius plots based on productivity and wage assumptions on similar sites as follows: 1.5–2.5 plots installed/day (all trees measured) by a forester working at a daily rate of \$270 would cost \$104–180/plot.

In addition to the contract price to acquire the data, the Malheur NF incurred costs to prepare and administer the contract, adding approximately \$1/plot to the total. The current federal salary schedule (2010) was used to estimate the costs of all tasks not paid directly under contract by assigning a grade level (midpoint, or step 5) consistent with the skill level required (Table 1) and multiplying by the number of hours. For example, processing the variable-radius plot data used the skills of a GS-12 working for 3 days. The cost of this processing was an additional \$792. When added to the acquisition costs of the variable-radius plot data (\$12,210), the total price of the stand exams was \$13,002. Unless otherwise stated, we used an average price of \$18.50/variable-radius plot and \$58/fixed-radius plot in our analysis of the Damon study data.

Remotely Sensed Data. LiDAR data were collected on September 15 and 16, 2007, by Watershed Sciences, Inc. (Corvallis, OR). The data were collected using a phase II laser (Leica ALS50) mounted in a Caravan 208B (Cessna). During the LiDAR survey, a static ground survey was conducted over monuments with known coordinates. One thousand seven real-time kinematic ground points were collected and compared with LiDAR data for accuracy assessment. The vendor achieved an absolute vertical accuracy of 0.024 m, a mean pulse density of 6.31 points/m^2, and a mean density of ground returns of 1.44 points/m^2.

The total area flown with LiDAR was 31,614 ac, which included a buffer area added first by the Malheur NF and then again by the vendor. The cost of acquiring LiDAR for the Damon project was \$1.35/ac. The time needed to acquire, process, and analyze these data is shown in Figure 2. A skilled GS-9 technician needed 1 week to process the LIDAR data and generate derived 20-m raster layers suitable as inputs for predictive mapping by imputation. The cost of this processing was an additional \$33,424. When added to the acquisition cost of the fixed-radius plot data (\$5,104) and the imagery (\$40,500), the total cost for LiDAR data in the Damon study was \$79,028.

Table 1. Cost for data collection and processing (LiDAR).

Processing task	No. of days	No. of hours	Worker grade level	Average rate ($/hr)	Average cost ($)	Minimum rate ($/hr)	Maximum rate ($/hr)	Minimum cost ($)	Maximum cost ($)
Data preprocessing	5	40	9	23	920	20	26	800	1,040
Project management	20	160	12	33	5,280	28	37.5	4,480	6,000
Remote sensing data	15	120	9	23	2,760	20	26	2,400	3,120
Field training data	2	16	9	23	368	20	26	320	416
Validation data	2	16	9	23	368	20	26	320	416
Geospatial join	1	8	9	23	184	20	26	160	208
Feature space	75	400	12	33	13,200	28	37.5	11,200	15,000
		200	9	23	4,600	20	26	4,000	5,200
Modeling	5	40	11	27	1,080	25	31	1,000	1,240
Spatial predictions	1	8	12	33	264	28	37.5	224	300
Validation	10	80	11	27	2,160	25	31	2,000	2,480
Product deliverables	10	40	9	23	920	20	26	800	1,040
		40	12	33	1,320	28	37.5	1,120	1,500
Total					33,424			28,824	37,960

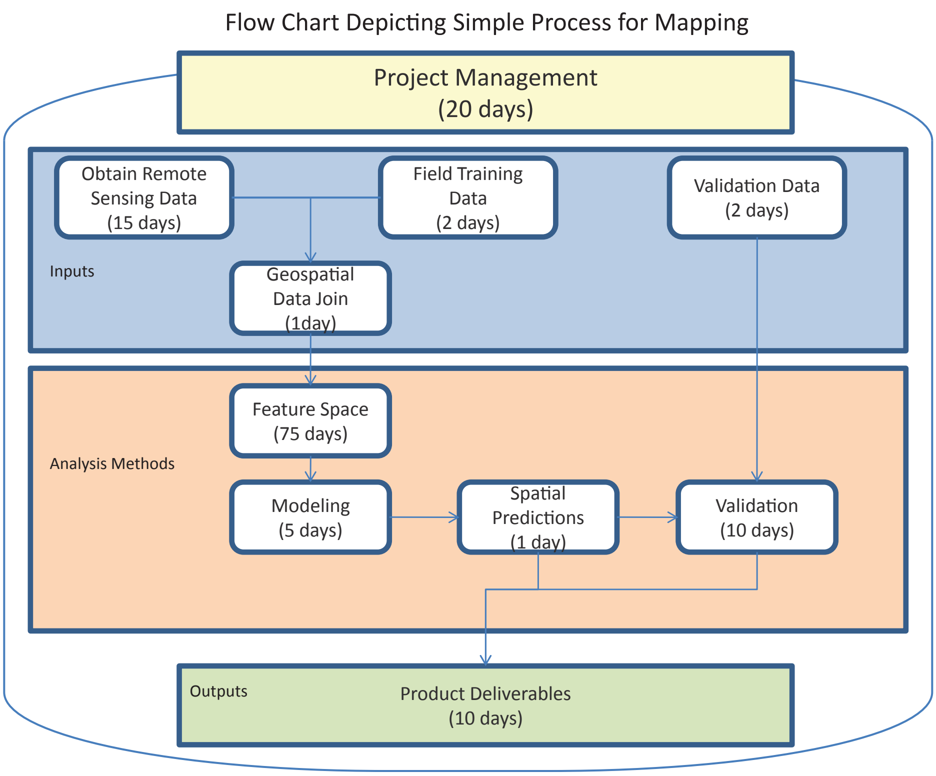

Figure 2. Flow chart for data processing and mapping.

Imputation of Forest Inventory Data

To impute our reference data to unsampled stands in the Damon study landscape, we used a model based on the random forest (RF) algorithm (see Breiman 2001, Lawrence et al. 2006, Prasad et al. 2006 for a detailed review of the RF algorithm). The RF algorithm is a robust, nonparametric classification and regression tree algorithm that can be used to quantify the proximity (multivariate distance) between reference and target observations (Crookston and Finley 2008). Falkowski et al. (2010) present a succinct overview of the RF imputation algorithm and its functionality. The RF algorithm calculates the proximity of each observation (reference and target) by developing classification tree ensembles (>100–>2,000). Observations that repeatedly occur in the same terminal node have a higher proximity than observations that do not occur in the same terminal node.

Overall proximity between each observation was calculated by dividing the number of times observations occur in the same terminal node by the number of classification trees in the ensemble. We selected the RF imputation algorithm because it has produced accurate predictions of stand-level BA and tree density (Hudak et al. 2008a) as well as tree-level forest inventory data (Falkowski et al. 2010) in similar study areas.

Reference Data. The 88 fixed-area plots were used as "reference" data or "training" data in the imputation process, which was executed at the 20 × 20-m pixel level (approximately the same size as a 1⁄10 ac fixed-radius plot). Every pixel within the study area as defined by the LiDAR survey was attributed with data from a single reference plot. Stand-level inventory data quantifying forest structure and volume were then generated by summarizing all imputed pixels within a stand; in this way, conditions in each of the 88 stands where validation data were collected were described. For continuous data, the arithmetic mean of a forest metric was used for all imputed pixels within each stand. The metrics derived from the reference plots included the following:

1. Structure.
   a. BA (ft^2/ac).
   b. Crown competition factor, relative measure of stand density.
   c. Quadratic mean diameter (QMD) (in.).
   d. Top height (TH) (Ft).
   e. Trees per acre (TPA), number of stems >5 in./ac.

2. Volume.
   a. Bd ft (number/ac).
   b. Biomass (dry tn/ac).
   c. Merchantable cubic feet (ft^3/ac).
   d. Total cubic feet (ft^3/ac).

Predictor Variables. The imputation models relied on both LiDAR and Landsat predictor variables available across the entire Damon study area. The LiDAR predictors included a suite of variables that have proven useful for the characterization of forest structure. Hudak et al. (2008a,b) and Falkowski et al. (2010) provide detailed description of the LiDAR-derived predictor variables plus the general methodology used to process the LiDAR data. The Landsat predictor variables included principal and independent components derived from all Landsat bands (sensor 5, scene location path 43, row 29, June–September 2008). All predictor variables had a spatial resolution of 20 m, which closely approximates the area of a 1⁄10-ac fixed-radius inventory plot.

A variable selection procedure was used to identify the optimal predictor variables for imputing forest structure and volume (see Falkowski et al. 2009, 2010). The procedure automatically selects the most important predictor variables by iteratively running the RF algorithm and subsetting classification variables based on a mean square error ratio threshold. The final variables were selected based on the criteria of smallest total and within-class errors and fewest numbers of variables. To stabilize individual class error, each RF model was run with 3,000 bootstrap replicates. These response variables were then imputed from 1 of the 88 training plots to each 20-m pixel, ultimately producing a map of all attributes of interest across the entire Damon study area.

Analysis

We first analyzed how the stand estimates made by using RF imputations compared with the estimates made by using summarized, variable-radius plot data. This addressed our main question: how data collected by using remote sensors compared with stand exam data for different volume and structure variables. Because we expected that the efficacy of different tests would vary according to the imputed or measured variable of interest, we used two: the *t*-test and the Wilcoxon paired signed-rank test (Wilcoxon test). To get started, we used the Anderson-Darling test (AD test) to check if our structure and volume variables came from a normal distribution. Then, a paired *t*-test examined the similarity between the stand-level summarized values and the imputed values. If the condition of normality in the AD test was met, values of $P \leq 0.05$ generated by the *t*-test indicate that the imputed and summarized values did not arise from the same distribution. If the condition of normality in the AD test was not met, the Wilcoxon test provided us with an (nonparametric) alternative to the paired *t*-test. The results of a nonparametric test can be used when one variable is distributed normally and the other is not. Like the *t*-test, the Wilcoxon test results in a *P*-value that gives a probability that the imputed and summarized values arise from the same distribution. Significant results ($P < 0.05$) indicate that the stand-level mean of the two methods (stand exam versus imputation) is different, whereas nonsignificance implies that the mean value is similar (not statistically different).

Next, we calculated the per acre costs of the variable-radius stand exam data and the LiDAR data for the Damon study. The costs to collect and process the stand exam data ($13,002) were distributed across the area sampled, which was 18% of the study area (5,280 ac). The total costs to acquire and process the LiDAR data ($79,028), including the fixed-radius field plots (18% of area) and the LiDAR imagery (100% of area), were distributed across the entire area (30,000 ac).

We also estimated a range of costs—from low to high and for areas increasing in size by 20,000-ac increments—for collecting and processing stand exam and LiDAR data. To calculate the minimum and maximum amount for collecting the stand exam data, we used the midpoint of the low price estimate ($20) and the high price estimate ($37) per plot, while holding constant the average stand size (60 ac) and plot density (1 plot/8 ac). For the fixed-area LiDAR "training" data, we used $104, 142, and 180/field plot to estimate minimum, average, and maximum prices, respectively. For acquiring LiDAR imagery, we assumed prices ranging from $1/ac (minimum) to $2/ac (maximum) with the midpoint ($1.5/ac) as average. For both types of data we assumed the same field sampling intensity (18% of area). Costs for processing the stand exam data and the LiDAR data were calculated by using the within-grade wage range in the 2010 federal government salary schedule (step 1 = low and step 10 = high). We added together the low estimates for data collection and processing (e.g., LiDAR: low plots = $9,152 + low imagery = $30,000 + low processing = $28,824) to estimate the total low cost per acre ($67,976/30,000 = $2.27/ac) stand exam: low plots = $13,200 + low processing = $672 = $13,872/5280 ac = $2.63/ac) and then repeated this summation for the high estimates (e.g., LiDAR: high plots = $15,840 + high imagery = $60,000 + high processing = $37,960 = $113,800/30,000 = $3.79/ac) to calculate the range, respectively, of low to high costs per acre.

Results

The data derived from stand exams were generally distributed normally; the three exceptions were structure variables (TH, TPA, and QMD). The structural variables for LiDAR tended to be nonnormally distributed with the exception of BA. In contrast, the volume variables were normally distributed except for biomass. Given these results from the AD test, we report only *P*-values from the Wilcoxon test.

Structure

Estimates of BA, TH, and TPA imputed from LiDAR predictor variables were not significantly different from the estimates made by summarizing stand exam data (Table 2). For BA and TH, the use of LiDAR as predictor variables produced mean estimates similar to the stand exams (Table 2). However, the mean LiDAR-based estimate of TPA was lower than the mean estimate from the stand exams (TPA LiDAR = 506; TPA stand exam = 624.6 [Table 2]).

Landsat-based imputations of BA and TH were significantly different from the stand exam estimates; Landsat underestimated both BA and TH. However, there was no significant difference between Landsat-based TPA estimates and those derived from stand exam data. In fact, the mean Landsat TPA estimate was closer to the stand exam mean estimate than was the LiDAR-based estimate of TPA.

Volume

The predictions of volume attributes made using LiDAR or a combination of LiDAR and Landsat imagery were more often significantly different from estimates derived from stand exam data. In fact, only the Landsat-imputed estimate of mean biomass was not significantly different from the mean stand exam estimate (Table 3). The intercepts (>0) indicate that the imputations generally overestimated at low volumes.

Cost

In the Damon study, the cost per acre to acquire and process the variable-radius stand exam data was $2.46 ($13,002/5,280 ac = $2.46/ac) compared with $2.63/ac to acquire and process the LiDAR data (Table 4). Estimates of the minimum and maximum cost per acre for an area similar in size to our study area (30,000 ac) suggest that this relationship would reverse, however, if a landowner were able to pay the lowest average price per fixed area plot ($104) and price per acre for LiDAR data ($1). In this event, the minimum cost per acre to acquire and process LiDAR data ($2.27; Table 4) would drop below the minimum cost to acquire and process stand exam data ($2.63).

As we increased the size of the analysis area by increments of 20,000 ac, the estimated cost per acre for LiDAR remained below the estimated minimum cost for stand exam data. When the analysis area reached 70,000 ac, our results suggest a landowner could pay $1.50/ac for LiDAR imagery and still incur an average cost per acre ($2.39; Table 4) to acquire and process inventory data over 100% of an area that was lower than the minimum cost per acre for stand exam data ($2.55) over just 18% of the area.

Table 2. Results of tests comparing structure LiDAR data with stand exam data.

Stand exam mean and Predictor variables	Mean	SD	Kurtosis	Slope	Intercept	*P*-value
BA						
84.1 (SD 40.7)						
LiDAR	83.1	24.5	−0.1	0.5	41	0.9
LiDAR + Landsat	83.3	29.1	−0.7	0.6	32	0.9
Landsat satellite	70.6	26	−0.9	0.5	26	0
TH						
57.7 (SD 18.9)						
LiDAR	60.4	12.5	0.7	0.58	27	0.09
LiDAR + Landsat	60.5	14.7	−0.1	0.69	21	0.03
Landsat satellite	52.1	14.3	−0.8	0.63	16	0.0
TPA						
624.6 (SD 461.5)						
LiDAR	506	214.9	−1.1	0.05	472	0.19
LiDAR + Landsat	815	304.8	−0.5	−0.18	926	0
Landsat satellite	611.6	246.5	1.6	0.25	457	0.33

Slope and intercept values are from least squares linear fit; kurtosis and *P*-values are from Wilcoxon test. A value of $P < 0.05$ indicates a significant difference between the stand exam and remote sensing approaches.

Table 3. Results of tests comparing volume LiDAR data to stand exam data.

Stand exam mean and Predictor variables	Mean	SD	Kurtosis	Slope	Intercept	*P*-value
Biomass						
38.1 (SD 20)						
LiDAR	29.1	8.2	−0.05	0.3	18	0.00
LiDAR + Landsat	33.2	10	−1.1	0.4	18	0.00
Landsat satellite	35.2	6.6	1.7	0.2	28	0.31
Bd ft						
7,995 (SD 5,147)						
LiDAR	8,959	4,501	0	0.5	3,006	0.00
LiDAR + Landsat	10,380	4,916	−0.6	0.8	3,800	0.00
Landsat satellite	7,151	3,420	−1	0.8	2,702	0.03
Total cubic feet						
1,883 (SD 1,096)						
LiDAR	2,028	866	−0.1	0.69	727	0.01
LiDAR + Landsat	2,204	975	−0.7	0.78	733	0.00
Landsat satellite	1,637	731	−1	0.55	603	0.00

Slope and intercept values are from least squares linear fit; kurtosis and *P*-values are from Wilcoxon test. A value of $P < 0.05$ indicates a significant difference between the stand exam and remote sensing approaches.

Table 4. Estimated per acre cost to acquire and process LiDAR data.

Area (ac)	Damon study costs ($/ac)	Minimum costs ($/ac)	Average costs ($/ac)	Maximum costs ($/ac)
30,000	2.63	2.27	3.03	3.79
50,000	NA	1.88	2.59	3.29
70,000	NA	1.72	2.39	3.07
90,000	NA	1.63	2.29	2.95

NA, not applicable.

Discussion

Our results suggest that LiDAR data—in combination with measured field plots and imputation modeling—can generate a stand-level forest inventory of structural attributes such as height and BA that is comparable with one produced solely from stand exams. On the Malheur NF, there was insufficient evidence that the means of the two samples were statistically different for these attributes. Furthermore, we learned that using parametric statistical tests to assess the accuracy of imputed, forest structure data at a stand scale could violate the key assumption of normality.

We can not find other published comparisons on the cost of creating a stand-level forest inventory by using field exams alone versus combining field data with remotely sensed data. Hence, there is no established method for allocating the actual costs of data collection and processing to a heterogeneous management unit or landscape study area. We used information on the cost of the Damon project both to evaluate the study itself and to develop estimates to inform future projects. When considering our range of estimated costs, it is important to note that the actual price per stand exam plot in our study is lower than the estimated mean minimum price because of local contractor efficiencies. In addition, we used the actual geographic area sampled by each method to allocate costs because it represents the spatial extent of collected data. Making different assumptions about the price per plot, the number of plots required, the area sampled, or the method for distributing costs will affect the range of the estimates.

We had anticipated that the estimates of structure and volume variables made by incorporating LiDAR into our imputations would be more similar to the stand exam data than they in fact were. This could be due to the location of sample plots relative to tree cover, because the over- and underestimation errors in the imputed summaries relate to forest heterogeneity. Although increased heterogeneity should add variability to the estimate derived from stand exams, the sample plot locations did not always capture the variability. This might stem from errors in GPS accuracy, which would lead to mismatches between the LiDAR and plot data or it could be from errors in the stand exams. Our assumption is that the stand exam data are a truthful representation of stand conditions. Although we used a forest growth model to summarize the stand exam data, we did not use it to make projections of stand development. The collection dates for the remote and the field data were nearly synchronized. Any significant time lag would create a need to match collection dates via model simulation, which would introduce another source of potential error.

Imputed plot measurements appeared to overestimate forest metrics in stands with low cover and underestimate in stands with high cover. Because landscape stratification was based on canopy closure, the study sample (both the variable- and fixed-radius plots) discriminated against sites without tree cover. A majority of the comparisons of stand exam versus LiDAR classifications had <25% difference in BA. However, a handful (nine stands) had >75% difference in BA. This suggests that we may have had too few training plots with sparse or no tree cover.

Imputation is desirable because by using measured values it can lead to reasonable and unbiased predictions if sample stands are well distributed across the range of variability in forest conditions. This is a prerequisite to any predictive modeling or mapping approach used to assign values to unsampled locations (e.g., regression). However, regression models can produce unreasonably high (or low) predictions and distort the tails in the distribution of predicted values relative to observations (Eskelson et al. 2009). In our analysis, much of the variability in forest conditions occurs within stands, which the 20-m imputed maps reasonably portray, but this variability gets greatly reduced when aggregated to the stand level. Aggregation effects may also explain why the stand-level predictions tended to cluster around the mean condition and why the Landsat-based imputations did not differ as much from the LiDAR-based imputations as initially expected.

The contribution of LiDAR data to the objectives of the Malheur NF for prioritizing landscape management activities was promising because we found insufficient evidence to suggest that the means of the two samples (stand exam versus imputed) for the structural variables of interest were statistically different. In addition, Malheur NF managers have benefited from the LiDAR data more than this analysis suggests. Data collected during the Damon study were used by planning staff to estimate forest cover and structure to identify target stands for fuel reduction treatments. In addition, lessons learned during the Damon project have motivated new contracts for LiDAR data collection across areas on the Malheur NF an order of magnitude larger.

We recognize that the geographic requirements (scale and level of detail) of forest management may well change in the future. Forest inventory information mapped at even finer spatial scales (e.g., 20-m cells instead of stands) could provide greater management flexibility. Depending on their own needs, managers could then aggregate the information to stands or to other mapped units, whether a woodlot or a watershed.

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