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Use of lidar-derived landscape parameters to characterize alternative harvest system options in the Inland Northwest

Ryer M. Becker[a], Robert F. Keefe[a], Nathaniel M. Anderson[b] and Jan U.H. Eitel[c]

[a]Forest Operations Research Lab, University of Idaho, Moscow, Idaho, USA; [b]Rocky Mountain Research Station, U.S. Forest Service, Missoula, Montana, USA; [c]Natural Resources and Society, University of Idaho McCall Outdoor Science School, McCall, Idaho, USA

ABSTRACT

As innovative harvest systems are developed, the extent to which they can be utilized on the landscape based on machine capabilities is often unclear to forest managers. Spatial decision support models may aid contractors and forest planners in choosing appropriate logging systems based on topography and stand characteristics. Lidar and inventory data from 91 sample plots were used to model site characteristics for 2627 stands in the Slate Creek drainage on the Nez Perce Clearwater National Forest in north-central Idaho, USA, and were integrated into a decision support model to compare harvest system selection using five harvest systems and three scenarios. In two of the scenarios, shovel harvester-based logging systems, which are not common in the area, were included to determine potential sites where integration of these systems is possible based on landscape and stand conditions. Lidar-derived predictions for volume and trees per hectare were determined with model accuracies of 76.4% and 70.3%, and together with topographic characteristics it was determined that shovel harvester-based options were feasible across a significant portion of the study area (31% and 34% in the two scenarios). Additionally, increasing operable slope for ground-based systems by 10% increased the area in harvestable classification by 21%. Harvest system classification using lidar-derived products and known system capabilities allows contractors and managers to better evaluate alternative harvest system options on landscape scales and may encourage the utilization of innovative machinery not currently integrated into most logging operations.

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Introduction

Harvesting system selection in forest operations is an integral component of applied forest management. Forest stands vary greatly in tree height, diameter, volume and topographic characteristics, resulting in a need for forest managers to effectively and efficiently select harvest systems best equipped to handle these varying conditions (Wang et al. 1998; Adams et al. 2003). Decades of forest operations research and industrial timber harvesting experience has led to general understanding of capabilities and operational thresholds of existing logging systems and their effective deployment. However, as technology advances and equipment evolves over time, the toolbox of available harvest systems from which to choose continues to grow, making it necessary for managers and contractors to stay informed about innovation in harvest systems (Kuhmaier & Stampfer 2010) and to better understand trade-offs among conventional and emerging options. It is also important to identify both specific stands and the potential total area for which newer options may be preferable. This is necessary because the choice of harvesting system has large impacts on costs, and machine and workforce capacity (Matthews 1942; Kühmaier & Stampfer 2010; Bell et al. 2017), especially in difficult terrain and marginal stand conditions.

Broken or irregular topography creates unique challenges in harvest system selection and planning that are largely driven by fine-resolution spatial patterns (Saralecos et al. 2014; Saralecos et al. 2015; Bell et al. 2017). These factors make operations in sensitive and steep terrain more complex than gentle terrain operations (Abbas et al. 2018) and these challenges are often associated with worker safety and logging production (Amishev & Evanson 2010). Ground-based systems are generally associated with higher production and lower costs, as compared to cable systems (Andersson & Young 1998; Strandgard et al. 2014). This makes innovative, ground-based, steep slope harvesting systems an appealing alternative to cable systems within feasible operational thresholds. Self-leveling chassis of harvesting machines increase safety, comfort of operation, and sustained high efficiencies on steep terrain when compared to fixed cab ground-based machines (Gellerstedt 1998; MacDonald 1999; Acuna et al. 2011). One such machine gaining popularity in logging operations is the self-leveling shovel harvester. These machines both fell and forward trees to the roadside, fulfiling harvest tasks typically completed by two separate machines.

Along with increased use of self-leveling shovel logging units in the Inland Northwest, contractors have also started incorporating tethered harvest systems into steep slope operations. With early work exploring tethered systems beginning

CONTACT Ryer M. Becker rbecker@uidaho.edu Forest Operations Research Lab, University of Idaho, Moscow, Idaho, USA

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in the early 1970s, tethered forestry equipment has since become commercially available in the United States (US) and has been so in Europe for over 15 years (McKenzie & Richardson 1978; Visser & Stampfer 2015; Sessions et al. 2017). Over the past 10 years, New Zealand has seen a significant increase in the use of winch-assist technology, with over 50 units actively operating (Abbas et al. 2018). There are now over 45 winch-assisted machines operating in North America as well; 23 of which are in the Pacific Northwest (Amishev 2017). These include systems incorporating either a dedicated cable-assist machine or an integrated winch mechanism on the harvester (Amishev & Evanson 2010; Visser & Stampfer 2015; Sessions et al. 2017). As use of tethered logging systems increases, so does the importance of efficiently and effectively characterizing the feasibility of logging system alternatives at harvest unit and landscape scales.

In the Inland Northwest US (eastern Washington, northern Idaho and western Montana), ash-capped soils are particularly susceptible to compaction and disturbance, increasing the demand for harvest practices that ensure their protection and meet sustainability certification standards (Page-Dumroese 1993; Johnson et al. 2005; Laukkanen et al. 2005). In response, the US Forest Service (USFS) restricts skidding on ground exceeding 35% slope, with other landowners across Idaho and the US employing similar restrictions (Greulich et al. 2001; Hollenkamp, personal communication, 2014; Barkley et al. 2015). However, low-impact, self-leveling machines may result in exceptions to existing restrictions if they are shown to operate below established thresholds for soil disturbance criteria. Additionally, tethered harvest systems may reduce soil disturbance by reducing track slippage, though few studies have quantified the actual impacts of these systems on previously undisturbed ground (Visser & Stampfer 2015).

In the context of precision forestry, incorporating new harvest system information into site-specific management and operations decision-making provides a valuable resource for long-term sustainability, improved logging production and better environmental quality protection (Eker & Ozer 2015). Precision forestry is a forest management technique that emphasizes data-intensive and innovative practices, technologies and processes to increase productivity, reduce costs, and reduce negative site impacts (Taylor et al. 2002; Kovacsova & Antalova 2010). However, the promise of precision forestry must be facilitated by decision support that is both accessible and appropriate for practitioners in the field.

Decision support systems are defined as any means or tools used to aid in decision-making processes (Acosta & Corral 2017). In forest operations research, decision support is often developed to define machine activity and harvest system classification. Past research has resulted in the development of various decision support systems for logging system selection based on terrain and site characteristics (Reisinger & Davis 1986; Davis & Reisinger 1990; Hartsough et al. 2001; Suvien 2006; Kühmaier & Stampfer 2010). In the context of steep, mountainous operations, various tools have been developed and have been applied operationally for varying harvest systems (Heinimann 1998; Stampfer et al. 2001; Chung et al. 2004; Largo et al. 2004; Acuna et al. 2011; Bell & Keefe 2014; Keefe 2014; Barger et al. 2015; Bell et al. 2017). Development of a harvest system selection and decision support model that effectively facilitates alternative logging system analysis on broken topography of the Inland Northwest region is challenging (Moye et al. 1988). However, increased application of self-leveling shovel systems and tether-matched harvest systems creates the need for a new descriptive harvesting classification and associated decision support. Quantifying topographic and forest metrics for management areas at high resolution is an important first step in this process.

Remotely sensed data, including light detection and ranging (lidar), has been used widely in forest management and research (Lefsky et al. 2002; Akay et al. 2009: Wulder et al. 2012). Advancements in the three-dimensional mapping of topography and forest characteristics using lidar has provided opportunities to further develop decision support tools utilizing these high resolution spatial data (Wulder et al. 2012; Eitel et al. 2016). Stand metrics and topographic products derived from lidar also facilitate extrapolation of such models to a landscape scale (Reutebuch et al. 2005). Inventoried forest plots and subsequent development of predictive models using random forest classification and regression methods with lidar data allow stand metrics such as stand density, merchantable volume and basal area to be processed for landscape scale analyses (Breiman 2001; Rodriguez-Galiano et al. 2012; Gan et al. 2015; Hudak et al. 2016). These topographic and site variables can be predicted and processed at resolutions as fine as 1 meter (Reutebuch et al. 2005).

While lidar has been widely used in forest inventory analysis, utilization of these data in the context of forest operations has not been widely explored. In forest operations, research using lidar has focused primarily on developing high resolution digital elevation models (DEMs) for forest road layout (Akay et al. 2004, 2009; Akay & Sessions 2005; Aruga et al. 2005; Alam et al. 2013). In one of the few examples focused on equipment operability, Alam et al. (2013) incorporated lidar-derived slope data for a simulation model of a self-leveling feller-buncher.

Our goal in this study was to develop an accurate decision support model using lidar-derived forest and topographic metrics for generalized harvest system selection at the landscape scale, and use it to determine where innovative, alternative harvest systems such as self-leveling shovel logging and tether-matched steep slope harvest systems are feasible alternatives to conventional logging systems for all 2627 stands in the Slate Creek management area of the Nez Perce-Clearwater National Forest. We also quantified the potential impact that introducing shovel logging and tether-matched systems had on the use of conventional systems (ground-based and cable operations), which may be displaced by the new systems. Giving classification priority to the shovel harvester provides insight into areas where this system can be deployed as an alternative to other, more widely used systems and areas where any possible benefits of shovel harvesting have the potential to be captured. High production and cost effectiveness of shovel logging increases its feasibility, even in mountainous terrain (Fisher 1999). Site impacts caused by shovel

logging are inherently less than other ground-based systems, making shovel logging a favorable alternative for sensitive sites (Fisher 1999; Egan et al. 2002; Sessions & Boston 2006). Self-leveling capabilities of new shovels increase safe, effective operating capabilities of the machines, making the use of shovel logging more feasible across a wider range of sites, especially in the Inland Northwest.

We hypothesized that the area of land classified as most appropriate for conventional feller-buncher and skidder operations would change when introducing ground-based shovel harvesting as an alternative logging system. We also hypothesized that introducing a tethered shovel system would impact the proportion of land previously classified as excaliner and hand felling in our harvest system classification for the study area. We expected lidar-derived products could provide the needed forest and topographic metrics to perform landscape-scale harvest system classification and thereby yield foundational data necessary for subsequent production and cost analyses, and forest planning, in subsequent analysis. If successful, having the ability to define trade-offs among relevant logging systems spatially using lidar could be very helpful for advancing sustainable forest management in ways that both improve efficiency and reduce adverse environmental impacts.

Materials and methods

Methods overview and study site

We developed a process for harvest system site classification based upon forest and topographic characteristics for five harvest systems within three varying scenarios of regional logging system capacity. This approach provides an opportunity for operations managers and harvest planners to perform direct comparisons between harvest systems to aid in the selection of feasible systems based on stand characteristics, terrain and machine parameters. The model classifies stands within the management area based on forest and topographic characteristics including stand stocking, merchantable volume, slope, aspect, and harvest unit dimensions. The study area is northeast of Riggins, Idaho, in the Nez Perce Clearwater National Forest and consists of over 30,000 hectares (74,000 acres) with 2627 delineated stands of mixed-conifer overstory. Mountain pine beetle (*Dendroctonus ponderosae*) and recent wildfires have impacted the region and influenced management strategies including, but not limited to, timber harvests, salvage harvests, and fuel reduction treatments. Clearcutting with reserves was the primary silvicultural prescription applied. Stands were previously delineated by the Nez-Perce Clearwater National Forest and spatial data were provided by the National Forest to use in the analysis. Stands are approximately 12 hectares (29.7 acres) in area, on average. Non-SI units have been converted to SI units where necessary throughout the analysis.

Lidar-derived stand metrics

To quickly generate stand stocking reports for the study area, traditional inventory methods for collecting stand data were augmented with analysis using lidar data. Data from 91 field inventory plots, each 20 × 20-meter (1/10 acre), were input into the USFS Forest Vegetation Simulator (FVS) (Dixon 2002) to summarize stand composition and structure. Plot data were collected previously by researchers with the USFS Rocky Mountain Research Station Forestry Sciences Laboratory, Moscow, ID, and are described by Vogeler et al. (2014). These inventory plots were collected in 2008 by the USFS. Only trees greater than and equal to the 15.24 cm diameter class (6-inch) were considered for further use in data processing to represent only potentially merchantable trees. Lidar metrics encompassing the same extent as inventory plots were also acquired. Lidar data were acquired through Idaho Lidar Consortium and represented point cloud files from a single 2006 lidar flight acquisition. Lidar was flown and initially post-processed by Watershed Sciences Inc. (2006) with an average native density of ≥ 4 points per m^2. These data allowed the development of random forest models aimed at determining the relationship between the inventory metrics in question (trees per hectare, basal area, and merchantable volume) and corresponding lidar metrics for the plots.

A random forest is an ensemble learning technique combining multiple decision trees into an overall ensemble. This process is comparable to a form of nearest neighbor approximation, which incorporates a bootstrapping algorithm with decision trees. While predictions from a random forest are limited to the range of training data used, they are run quickly and are capable of dealing with unbalanced and missing data (Breiman 2001). Rapid processing capabilities and robustness of the ensemble learning method, even with missing values, were primary factors in choosing to use the random forest approach. Three separate random forest models to estimate field plot-derived stand density, merchantable volume and basal area from lidar metrics were built using the randomForest package (Liaw & Wiener 2002) in the statistical programming environment, R version 3.3.3 (R Core Team 2016). Additionally, the rfUtilities package (Evans & Murphy 2017) was used to optimize predictor variable selection during model development.

After random forest models were developed, they were then applied to the Slate Creek study area, which is 30,042 hectares. Files were processed using the U.S. Department of Agriculture (USDA) lidar processing software, FUSION version 3.60. An identical lidar post-processed data structure to those of 91 existing training plots was developed using FUSION to allow the random forest models built from the 2/3 training data and later validated using the remaining 1/3 test data set to be applied directly to the entire study area. Raster layers of predicted basal area, merchantable volume and stand density at 20 × 20-meter (1/10 acre) resolution were developed.

Shapefiles representing delineated stands for the entire study area were used to create boundaries for application of the harvest system selection model. Raster files for the complete study area where then split and delineated to the extent of each of the 2627 stand shapefiles populated in a single feature class. Average values for stand slope, trees per hectare, basal area (m^2ha^{-1}), and merchantable volume (m^3ha^{-1}) were determined for each of the 2627 stands using the lidar-

derived stand and slope metrics. Stand-level averages for forest and site metrics (merchantable volume, stocking density, basal area, slope, and aspect) were then determined across the study area. All lidar-derived and additional spatial data sources incorporated into the study analysis and interpretation are shown in Figure 1.

Harvest system classifications and forest and topographic metric classifications

Three landscape scale harvest system scenarios were addressed through the analysis process, representing implementation of five varying harvest systems across the Slate Creek study area in different combinations (Figure 2). Performing landscape scale queries of stand and site characteristics for various combinations of harvest equipment provided insight into the way in which new harvest system introduction across the landscape impacted distribution and area of feasible harvestable land for each system described. Three harvest systems remained constant in the three scenarios: feller-buncher with wheeled skidder; hand felling with excaliner skid; and hand felling with swing yarder skid. In the second scenario, a shovel harvester system, which includes felling and forwarding with a single machine, was included in the analysis. Operational threshold of the shovel harvester overlapped with that of the feller-buncher and wheeled skidder system. However, the shovel harvester was the preferred system when performing harvest system selection query across the 2627-study area stands to show the feasible extent of the innovative shovel system, though not necessarily the optimal system distribution.

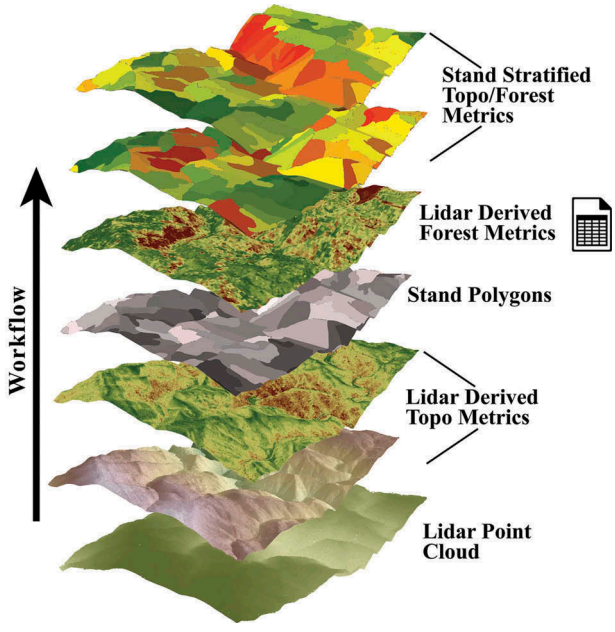

Figure 1. Multi-input spatial data sources for harvest system selection model.

In the third scenario, four harvest systems previously referenced in the second scenario were incorporated. A tethered shovel harvester system was added to the analysis. Any instances where the operational threshold of the tethered shovel harvester system overlapped with existing harvest system thresholds, the tethered system was used as the preferred system. Again, this classification priority given to the tethered shovel was used to determine areas where the tethered shovel is a feasible alternative to the excaliner and where incorporating the ground-based system may yield potential benefits. Higher production and lower costs of ground-based harvesting systems as opposed to cable counterparts (Fisher 1999) is the justification behind this approach.

Analyzing harvest systems and identifying their limiting parameters has been successfully described by decision support models using systems analysis (Talbot et al. 2003). To delineate stands in each scenario by each harvest system, operational thresholds were defined for each of the systems and were the foundation of the classification process. Operational thresholds for slope, forwarding/skid distance and minimum merchantable volume were defined for all systems (Table 1). The shovel harvester harvest system, independent of other machinery, was limited to forwarding distances not exceeding 180 meters (Krume, personal communication 2015; Fisher 1999). Forwarding distance for manual felling with excaliner yarding systems was restricted to distances not exceeding 250 meters. Any stand with a slope exceeding 35% and a forwarding distance exceeding 250 meters in variant A was consistently classified across all three scenarios as hand fell and swing yarder skid. This slope was increased to 45% in variant B. In all three scenarios, stands not exceeding 35% slope and exceeding 180-meter forwarding/skidding distance were classified as feller-buncher and wheeled skidder in variant A. This lower slope limit was increased to 45% in variant B. This was also the case in scenario 1 for stands below 180-meter forwarding/skidding distance.

The tethered shovel harvester system was bound by the same operational thresholds as the untethered shovel harvester apart from allowable operable slope. In this instance, operable slope began at 35% in variant A and 45% in variant B and was restricted to a maximum of 80% (Cavalli 2015). For each of the previously described

Figure 2. Harvest system options for stand classification (left to right): feller-buncher/grapple skidder; shovel harvester; tethered shovel harvester; excaliner/hand fell; swing yarder/hand fell.

Table 1. Harvest system scenarios for varying management situations. 29 m^3ha^{-1} was the minimum allowable stand merchantable volume for any unit to be considered harvestable.

Harvest System	Variant	Operable Slope	Forwarding/Skidding Distance
Scenario 1			
Buncher/Skidder	A	0 – 35%	</> 180 m
	B	0 – 45%	</> 180 m
Excaliner/Hand Fell	A	> 35%	< 250 m
	B	> 45%	< 250 m
Swing Yarder/Hand Fell	A	> 35%	> 250 m
	B	> 45%	> 250 m
Scenario 2			
Buncher/Skidder	A	0 – 35%	> 180 m
	B	0 – 45%	> 180 m
Shovel Harvester	A	0 – 35%	< 180 m
	B	0 – 45%	< 180 m
Excaliner/Hand Fell	A	> 35%	< 250 m
	B	> 45%	< 250 m
Swing Yarder/Hand Fell	A	> 35%	> 250 m
	B	> 45%	> 250 m
Scenario 3			
Buncher/Skidder	A	0 – 35%	> 180 m
	B	0 – 45%	> 180 m
Shovel Harvester	A	0 – 35%	< 180 m
	B	0 – 45%	< 180 m
Tethered Shovel	A	35 – 80%	< 180 m
	B	45 – 80%	< 180 m
Excaliner/Hand Fell	A	> 35%	< 250 m
	B	> 45%	< 250 m
Swing Yarder/Hand Fell	A	> 35%	> 250 m
	B	> 45%	> 250 m

harvest system scenarios, operational thresholds for slope and maximum skidding/forwarding distance are shown in Table 1. In all instances, minimum merchantable volume for classified stands was 29 m^3ha^{-1} (5000 BF/acre). Any stand with mean volume below this minimum bound was excluded from harvest system classification due to the infeasibility of performing a harvest in a stand with such low merchantable volume. In practice, these operational thresholds are flexible and can be tailored to the specific situation. Other limiting parameters can be substituted into the analysis, depending on agency best management practices, management objectives or other factors, and the method allows for customization of the harvest system capabilities and resulting classification.

For the purposes of this study, it was assumed that all skidding and forwarding for all harvest systems would occur directly parallel to the average azimuth aspect of the stand. Therefore, all skidding and forwarding occurred either directly up or downslope. To facilitate rapid and efficient measurements of all stands, an R script was developed that calculated all maximum forwarding or skidding distances. All code development was completed in the statistical programming environment R. With the aspect of each stand known, the script performed a sweep perpendicular to the aspect at 50 points along the width of the stand polygon measuring distance. Maximum forwarding or skidding distance within the polygon shapefile was then determined. With all necessary forest and site metric data available for the harvest system classification for the three scenarios, classification queries were developed and executed in ESRI (Redlands, CA) ArcMap version 10.3.1 Maps and resulting attributes were collected from the analysis providing both visual and tabular results from the harvest system classifications.

A sensitivity analysis was performed to determine the impact varying slope predictions had on the harvest system classification process. The stand level, average slope predictions were adjusted ± 15% at 2.5% intervals for scenarios 1 through 3 for variant A and harvest system classification was assessed again for each of the adjusted slope predictions.

It was understood that when applying this methodology for harvest system classification the large number of ground plots used to train and test random forest models for forest metrics in our study may not be available. To address this concern, we used simulation to evaluate the effect of sampling intensity on random forest model accuracy and strength. Models were developed for stand density, basal area and merchantable volume following the same methodology previously used. Sample sizes for these simulations ranged from 10 to 90 plots in increments of 2. For each sample size, random forest models were fitted for 1000 iterations to obtain mean values and 95% bootstrap-based confidence intervals for RMSE, R-squared, accuracy and mean estimate.

Results

Stand-level predictions across the 2627 stands for density, basal area and merchantable volume are shown in Figure 3. These stand level estimates were calculated from the random forest model predictions in 20 × 20-meter resolution raster datasets for each of the forest metrics and for the average slope topographic metric. Table 2 shows quality estimates for the random forest models developed for density, basal area, and merchantable volume in terms of the mean estimate value, root mean square error (RMSE), R-squared and model accuracy. For all random forest models, the RMSE was less than 50% of the prediction means for forest metrics,

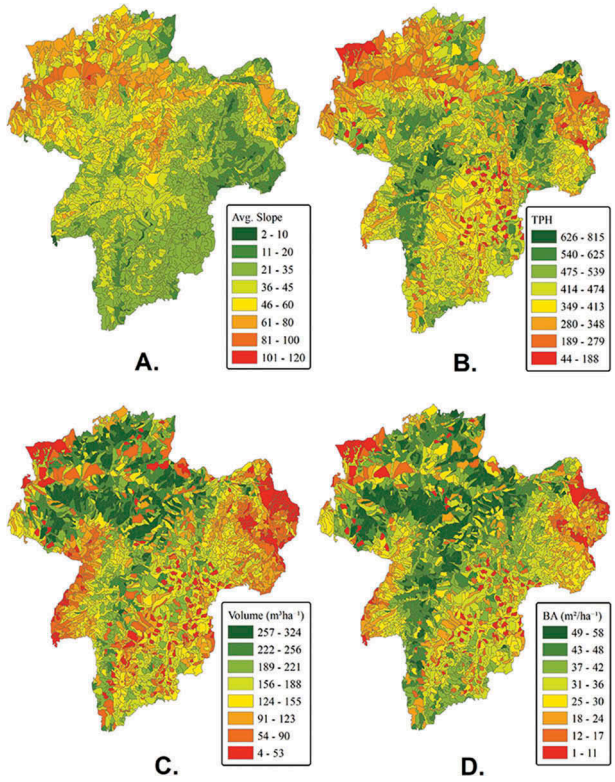

Figure 3. Stand-level averages for lidar-derived forest and topographic metrics for Slate Creek study area. See Table 2 for accuracy assessment of lidar-derived metrics.

Table 2. Random forest model quality assessment.

Random Forest	Prediction mean	RMSE	R-squared	Accuracy (%)
Stand density	405.57 tph	200.08	0.54	70.3
Basal area	36.57 m^2ha^{-1}	12.71	0.65	79.3
Merchantable volume	180.69 m^3ha^{-1}	78.66	0.56	76.4

which is within the range considered acceptable for our analysis. Random forest models developed to predict forest metrics across the study area returned accuracies exceeding 70%. These accuracies are comparable to those achieved in lidar-based random forest models developed by Falkowski et al. (2010) and Hudak et al. (2016). Model accuracies were 70.3%, 79.3% and 76.4% for stand density, basal area, and merchantable volume forests, respectively.

Spatial analysis and querying of forest and topographic metrics derived from lidar analysis produced maps of the three harvest system scenarios (Figure 4). From the maps, it is clear that introduction of additional harvest systems in Scenario 2 and Scenario 3 results in a recognizable difference in classification of harvest systems across the 30,042-hectare (74,232 acre) study area in both variant situations (Figure 4). Overall, introduction of the shovel harvester system in Scenario 2 resulted in a change of areas classified as feller-buncher and skidder of −31% and −46% of the overall area for variants A and B, respectively. For both variants, area reclassified from the feller-buncher and skidder system was alternatively reclassified to the shovel harvester system (Table 3).

Between Scenario 2 and Scenario 3, the tethered shovel system was introduced as an alternative to the excaliner and hand fell system, resulting in a decrease of area classified as excaliner and hand fell system of −34% and −19% of the overall study area for variants A and B, respectively (Table 3). A change of classification of 10,260 hectares (25,359 acres) for variant A and 5830 hectares (14,405 acres) for variant B from excaliner/hand-fell to tethered shovel is shown.

In all instances, the swing yarder and hand-fell system remained constant for stand and area classification because the swing yarder and hand-fell system is used in stands that exceed the maximum forwarding distance for all other harvest systems in this study, resulting in no feasible alternative. In addition, the number of stands and resultant hectares classified as "no harvest" also remained constant through all scenarios.

Adding 10% slope to the operable slope limit in variant B resulted in an increase of land classified as ground-based logging systems (feller-buncher/skidder) of 6132 hectares (15,144 acres) or 21% for Scenario 1. In Scenario 2, there were an additional 4334 hectares (10,703 acres) classified as shovel harvester in variant B than in variant A. In Scenario 3, there were an additional 4430 hectares (10,954 acres) classified as tethered shovel in variant A than in variant B due to higher area initially characterized as steep slope, cable ground.

Variant A resulted in an initial ground-based harvest system classification of 42% of the overall study area, with 54% classified as cable harvest and the remaining 4% defined as no harvest. These percentages remained consistent through all three scenarios when comparing ground-based and cable or cable-assisted systems. In variant B harvest system classification, the additional 10% slope added to the upper bounds of operable slope of the ground-based systems and resulted in an overall classification of 63% for ground-based system and 33% for cable system classification.

Results from the additional random forest model quality assessments are shown in Figure 5 for the stand density random forest model, Figure 6 for the merchantable volume random forest model, and Figure 7 for the basal area random forest model. From Figures 5, 6 and 7, it is evident that RMSE decreases and R-squared values increase for all three models, which is indicative of improving model prediction accuracy. In several instances, R-squared is a negative value at low sample sizes and represents very poor model fit. As the number of sample plots increased, variation between prediction means for all forest metrics between subsequent plots became more consistent. With a larger number of sample plots, the overall variability of the study area was better represented and random samples of predominantly high or low values were less likely to skew the data. Accuracies of the models stayed relatively consistent for all sample sizes, though less variability was found between subsequent numbers of sample plots once sample sizes increased. This indicates that

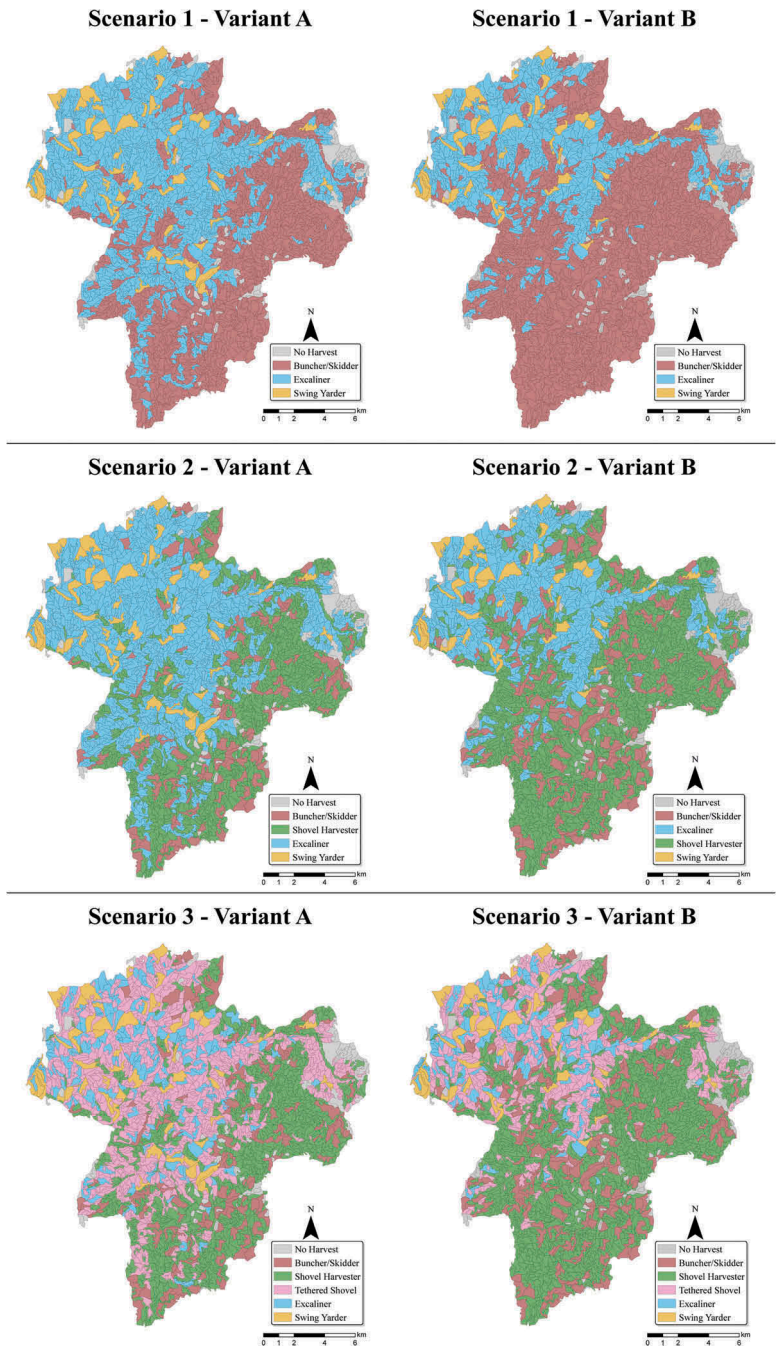

Figure 4. Harvest system selection maps for two variations of three harvest scenarios.

larger sample sizes produce more consistent random forest models for forest metric predictions. For all forest metrics and accuracy assessment metrics, it appears values became more consistent and improved when the sample plot number exceeded approximately 35 plots.

The sensitivity analysis results for the lidar-derived slope predictions are found in Figure 8. In general, the area and number of stands assigned to different harvesting systems was quite sensitive to the slope determination, with dramatic trade-offs between alternative systems in some cases. These results are a clear indication of the impact inaccurate slope predictions can have on the harvest system classifications and indicate the importance of accurate initial slope predictions. Fortunately, accurate elevation and slope determination is one of the strengths of lidar.

Discussion

Our method of using lidar to characterize stand characteristics and select logging systems, as well as compare alternative harvest options prior to field layout and implementation, proved effective. In variant A of the harvest system classification analysis, we found ground-based shovel logging was a feasible alternative to the feller-buncher system in 1062 stands. Comparatively, ground-based shovel logging systems provided a viable alternative to the feller-buncher and grapple

Table 3. Harvest system classification summary table for two variants of three scenarios.

Harvest system	Stands		Hectares (acres)		Area proportion	
Scenario 1						
Variant	A	B	A	B	A	B
No Harvest	91	91	1109 (2740)	1109 (2740)	0.04	0.04
Feller-Buncher/Skidder	1201	1,726	12,811 (31,657)	18,940 (46,801)	0.42	0.63
Excaliner/Hand Fell	1278	767	14,049 (34,716)	8,422 (20,810)	0.47	0.28
Swing Yarder/Hand Fell	57	43	2073 (5119)	1571 (3881)	0.07	0.05
	2627	2627	30,042 (74,232)	30,042 (74,232)	1.00	1.00
Scenario 2						
Variant	A	B	A	B	A	B
No Harvest	91	91	1109 (2740)	1109 (2740)	0.04	0.04
Feller-Buncher/Skidder	139	218	3425 (8463)	5222 (12,904)	0.11	0.17
Shovel Harvester	1,062	1,508	9386 (23,194)	13,718 (33,897)	0.31	0.46
Excaliner/Hand Fell	1,278	767	14,049 (34,716)	8422 (20,810)	0.47	0.28
Swing Yarder/Hand Fell	57	43	2073 (5119)	1571 (3881)	0.07	0.05
	2627	2627	30,042 (74,232)	30,042 (74,232)	1.00	1.00
Scenario 3						
Variant	A	B	A	B	A	B
No Harvest	91	91	1109 (2740)	1109 (2740)	0.04	0.04
Feller-Buncher/Skidder	139	218	3425 (8463)	5222 (12,904)	0.11	0.17
Shovel Harvester	1,062	1,508	9386 (23,194)	13,718 (33,897)	0.31	0.46
Tethered Shovel	1,064	618	10,262 (25,359)	5830 (14,405)	0.34	0.19
Excaliner/Hand Fell	214	149	3787 (9357)	2592 (6405)	0.13	0.09
Swing Yarder/Hand Fell	57	43	2073 (5119)	1571 (3881)	0.07	0.05
	2627	2627	30,042 (74,232)	30,042 (74,232)	1.00	1.00

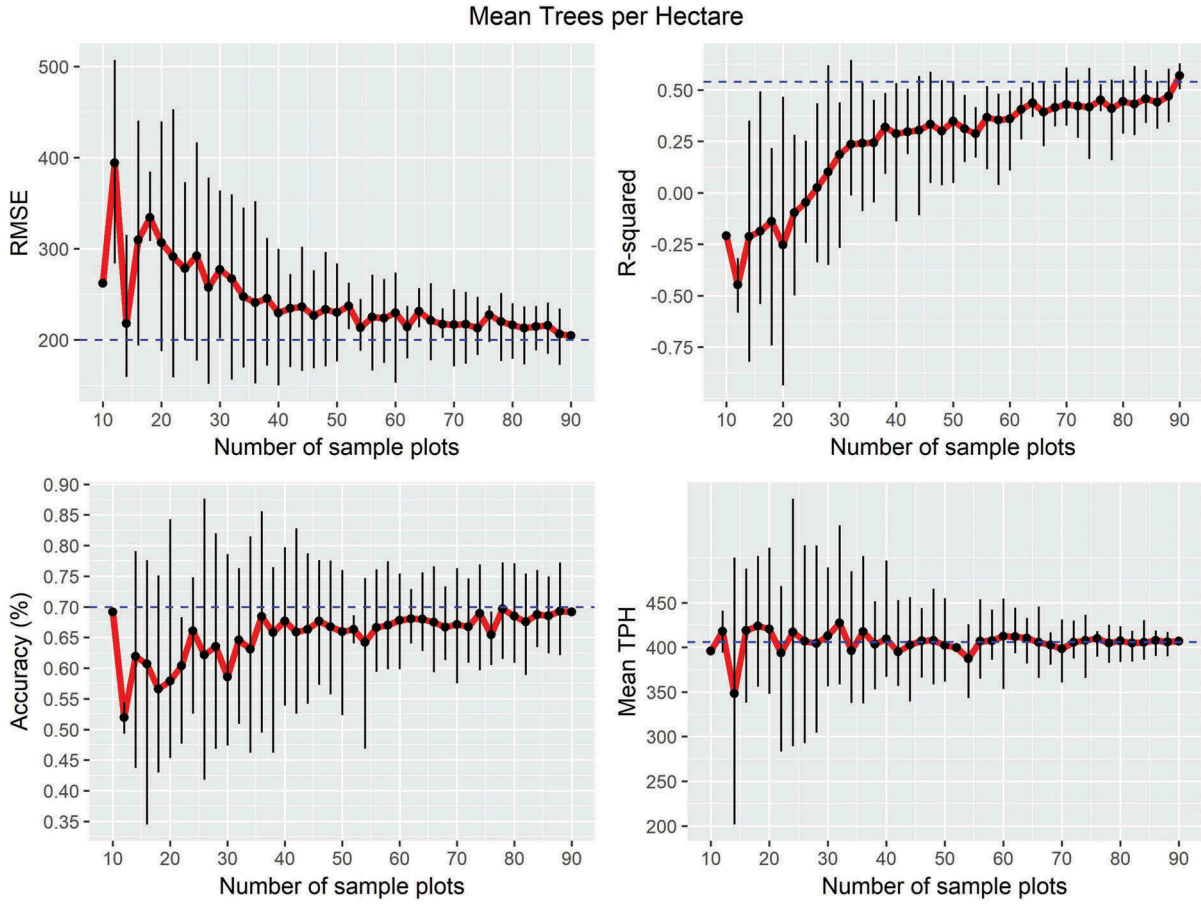

Figure 5. Root mean squared error (RMSE), R-squared, accuracy and prediction mean plots for mean stand density (trees per hectare) random forest model representing sample plots of 10 up to 90 increasing by 2. Horizontal line represents values for model using all 91 plots. Confidence intervals (95%) are shown using black bars at each sample size.

skidder in variant B in 1508 stands. Similarly, the tethered shovel harvester system was found to be a viable alternative to the excaliner in 1064 stands for variant A and 618 stands for variant B.

From an operational standpoint, potential implementation of the shovel harvester as an alternative to the feller-buncher and grapple skidder system means one machine could be used to harvest these stands rather than two. This may lead to

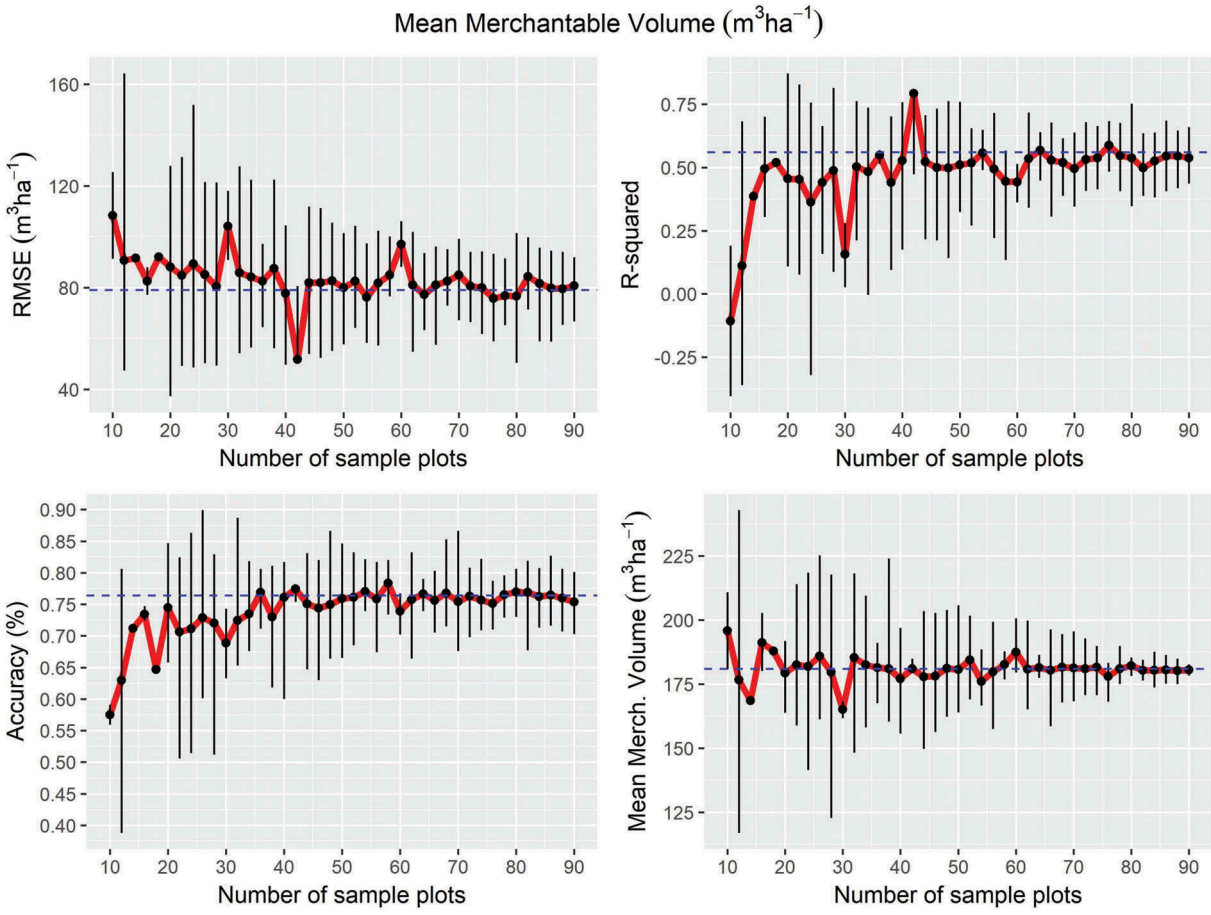

Figure 6. Root mean squared error (RMSE), R-squared, accuracy and prediction mean plots for mean merchantable volume (m^3ha^{-1}) random forest model representing sample plots of 10 up to 90 increasing by 2. Horizontal line represents values for model using all 91 plots. Confidence intervals (95%) are shown using black bars at each sample size.

lower fuel, labor and maintenance costs, potentially resulting in lower total logging costs, depending on system productivity. For example, based on information provided by logging contractors, Fisher (1999) determined that shovel logging reduced unit costs by 40% compared to some cable alternatives, including a slackline tower and swing yarder. More generally, having the ability to match an appropriate harvest system with operability constraints of forest and topographic conditions is the first step in increasing productivity and reducing costs. However, stand-level logging costs for the two systems should be estimated and compared prior to decision-making about optimal or preferred options. Without performing production and cost estimation, the classifications in this study are aimed at describing the extent of feasible stands for the innovative, ground-based harvest systems based on operable thresholds and not necessarily the optimal system for each stand.

Increasing the slopes on which ground-based harvest machinery is allowed to operate, especially within the US National Forest System, is an important consideration when attempting to maximize timber production in treated stands under conditions that are safe for modern equipment. Increasing the upper bounds of operable slope for the ground-based systems by 10% slope resulted in an increase in overall operable ground of 21% of our study area. This equated to over 6300 ha. Increased safety associated with mechanized felling using tethered and untethered shovel harvesters, in comparison to hand felling, which is less safe, is an important benefit when considering increasing allowable slopes of ground-based systems (Kim et al. 2017). This is especially relevant in the context of the Slate Creek study area, where beetle killed stands present hazardous working conditions for ground workers, especially from falling wood and breakage during felling. Classifying feasible stands to incorporate these alternative harvest systems means fewer workers outside the protection of enclosed machine cabs.

Ground-based shovel harvester systems, both tethered and untethered, are gaining traction as popular harvest methods in the Inland Northwest. Delineating areas where specific harvest systems can be used appropriately may in turn promote effective forest management by creating safer working conditions, reducing costs and increasing logging productivity. This is done by providing tools to facilitate efficient and effective decisions that consider forest characteristics and topographic features, as well as innovative technologies and processes, when managing individual stands and larger landscapes.

The accuracy with which forest and topographic metrics can be derived and predicted from lidar data for use in resource management is increasing (Reutebuch

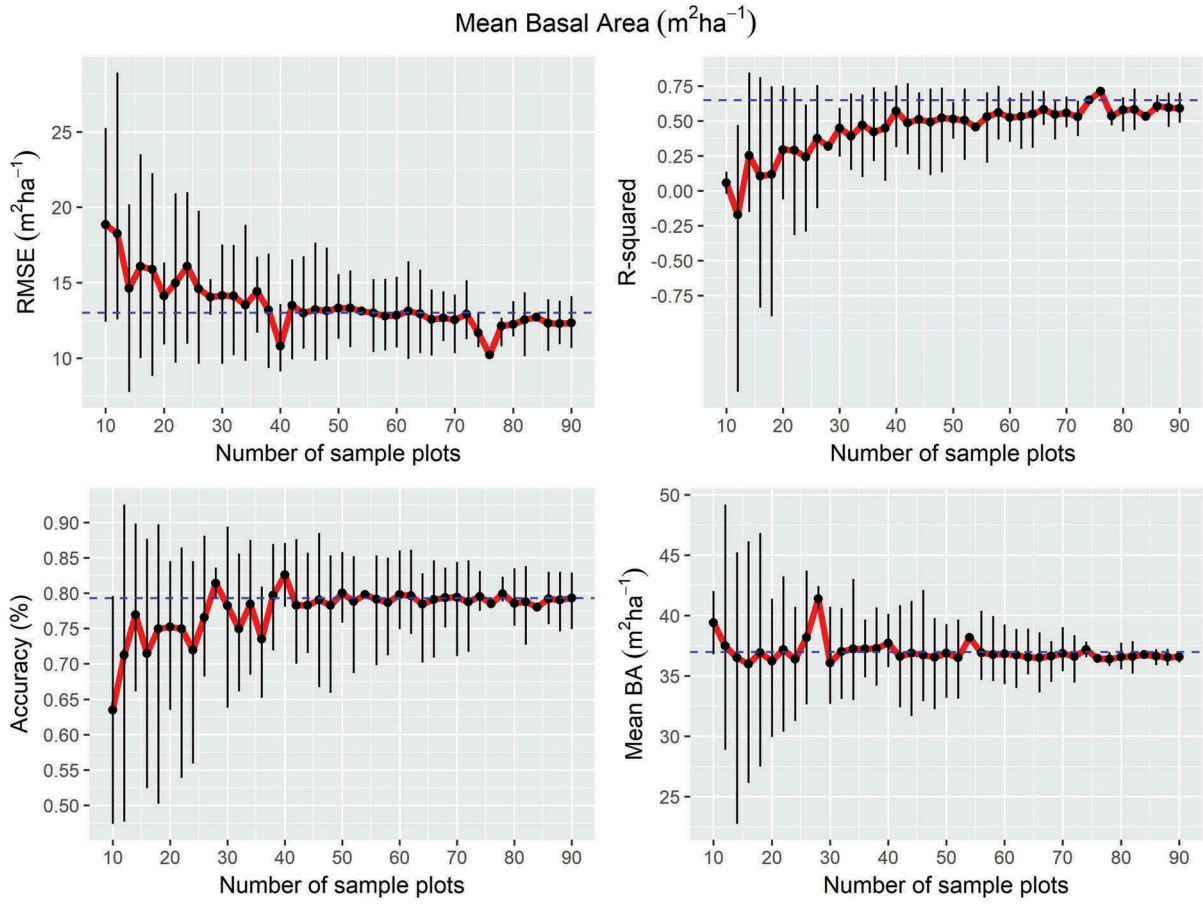

Figure 7. Root mean squared error (RMSE), R-squared, accuracy and prediction mean plots for mean basal area (m^2ha^{-1}) random forest model representing sample plots of 10 up to 90 increasing by 2. Horizontal line represents values for model using all 91 plots. Confidence intervals (95%) are shown using black bars at each sample size.

et al. 2005). Development of automated algorithms for detecting and delineating individual tree crowns has made the application of these data in precision forestry more feasible (Zhen et al. 2016). Furthermore, research delineating individual tree locations and individual tree volume estimation continues to advance our understanding and utilization of lidar data and other remotely sensed information and provides opportunities to advance precision forestry in innovative ways (Falkowski et al. 2006; Chen et al. 2007; Akay et al. 2009; Gupta et al. 2013; Zhen et al. 2016; Barnes et al. 2017). Methods to improve the accuracy of these predictions, however, still need to be developed and commercial applications are limited. We have shown that lidar provides a valuable tool for predictions and depictions of stand scale and landscape scale harvest system classification. However, to fully take advantage of emerging high-resolution lidar characterization of forest products, subsequent research should focus on simulating logging at the individual-tree level in ways that can provide meaningful analysis and information to inform equipment operators. Additionally, the impact of micro-site variability was not assessed in our analysis, but should be addressed to improve the effectiveness of the harvest classification model.

The random forest model assessment performed provides the basis for the assumption that comparable random forest models and resulting prediction accuracies can be achieved with access to fewer training and testing plots than used in this study. However, accuracies of model predictions may be adversely impacted once the number of sample plots drops below a certain threshold, as shown in our analysis. It is unclear from our analysis what stand or geographic factors may affect this threshold.

As seen from the sensitivity analysis performed for predicted slope, taking steps to ensure accurate classification metric predictions is important in assuring an overall accurate assessment of harvest system classification using this approach. The impact of error and uncertainty in predicting slope is dramatic (Figure 8), especially in the context of cable- versus ground-based harvest systems. Accessing updated and recent lidar acquisitions help ensure high density returns and better resultant predictions, as does the development of effective random forest models.

Efficiently performing harvest system classifications at the landscape scale using lidar-derived metrics will lead to continuing work further utilizing these data in an operational context (Figure 9). Combining these classifications with stand-level logging cost estimates in future work will provide

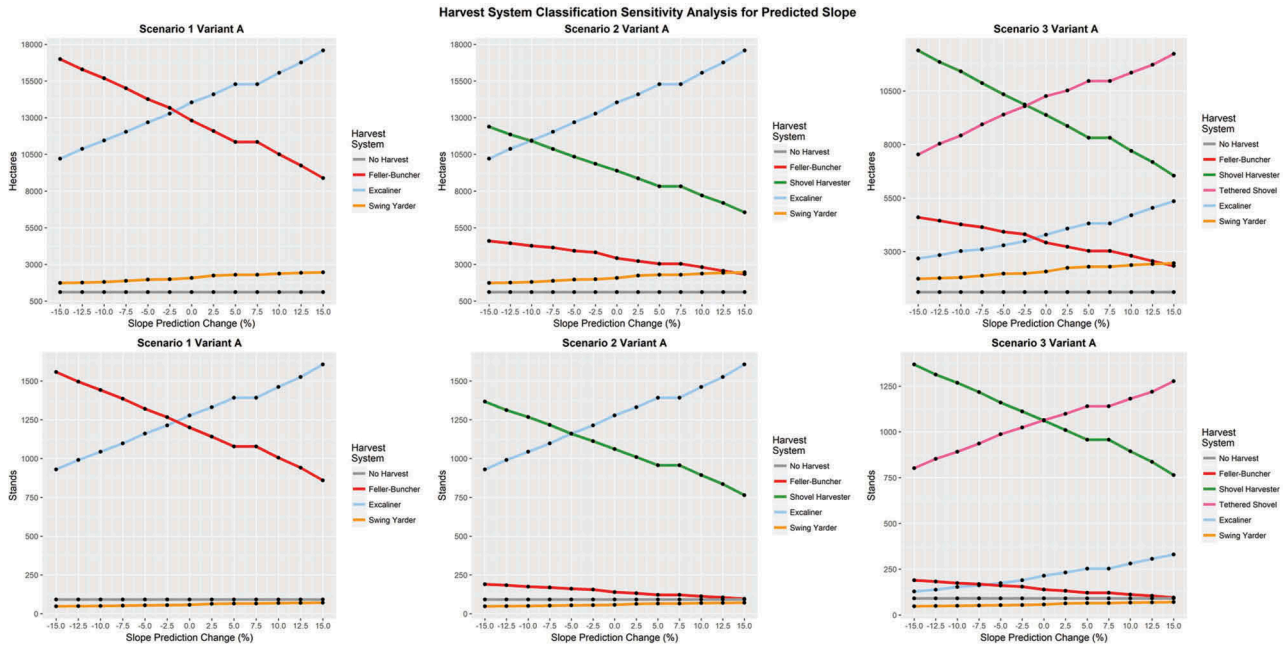

Figure 8. Sensitivity analysis of predicted slope ±15% for number of hectares and stands classified by harvest system for scenario 1 through 3 for variant A. From 5% to 7.5% adjusted slope, hectare and stand values did not change because no stands existed where the increased slope values resulted in differing classification in that range.

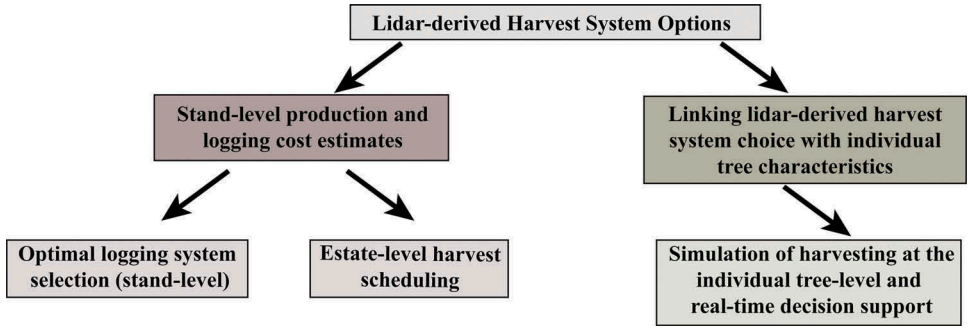

Figure 9. Future work addressing operational applications from lidar-derived harvest system classifications.

the basis for determining the optimal harvest system at the stand-level in subsequent analyses. To increase the usefulness of this approach, stand-level production and logging cost estimates can provide the foundation for performing estate-level harvest scheduling analysis with stand-specific logging cost estimates, rather than assumed values.

Lidar-derived harvest system classifications can also be integrated with individual tree-level harvest simulation and real-time decision support, further building on the foundational work developed in this study. Keefe et al. (2014) outlined the use of geographic navigation satellite system with radio frequency communication (GNSS-RF) as a method to support real-time analysis and model-based decision support in forest operations. Becker et al. (2017), Wempe & Keefe (2017), Grayson et al. (2016), Zimbelman et al. (2017) and Zimbelman and Keefe (2018) have contributed to the development of new applications of GNSS-RF technologies in operational forestry and logging safety. Use of lidar-derived forest and topographic metrics for harvest system selection described in this study and the subsequent development of individual tree level, within-stand simulation of logging systems derived from LiDAR, will further advance precision forest operations as LiDAR-based stand characteristics and real-time analytic models are merged.

In conclusion, as technologies and equipment continue to advance, foresters, engineers, loggers, and forest planners can increasingly utilize and incorporate lidar analysis and lidar-derived products into current practices to increase harvest productivity, minimize costs, and encourage long-term sustainable forest management practices. Our results showed significant potential for characterizing the appropriateness of sites for new logging systems at the stand and landscape scales, and should be further developed in future studies. A clear understanding of not only the capabilities of remotely sensed data, but ways to effectively incorporate these into operational forestry is critical for capturing the potential benefits these data sources provide. Precision forestry has long been a motivating

concept that has lagged in application and execution in practice. However, methods and products developed in this study combine remotely sensed data capabilities to address management challenges and actualize the concept of precision forestry in forest operations.

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Disclosure statement

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ORCID

Jan U.H. Eitel http://orcid.org/0000-0003-1903-3833

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