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Validation of the OpCost logging cost model using contractor surveys

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ABSTRACT
OpCost is a harvest and fuel treatment operations cost model developed to function as both a standalone tool and an integrated component of the Bioregional Inventory Originated Simulation Under Management (BioSum) analytical framework for landscape-level analysis of forest management alternatives. OpCost is an updated implementation of the Fuel Reduction Cost Simulator (FRCS). However, neither FRCS nor OpCost have been formally validated. Validation of simulation models using data that are independent of those used for model development is important for building user confidence in model predictions. This is particularly true when models are embedded in decision support systems and deployed regionally to inform policy. To evaluate the quality of OpCost predictions in fuel reduction treatments, a mixed method survey was conducted in Oregon, Washington, and Idaho. Professional logging contractors were asked to estimate the production rates and costs of common logging systems using timber sale prospectus data generated using GIS and the FVS model. Comparing survey results to production and cost estimates generated by OpCost for the same stand and site conditions facilitated evaluation of prediction error for both entire harvest systems and their individual equipment components. Model predictions were not different from expert estimates of total costs for harvest systems, but there were differences between predicted and expert estimates of production rates for individual pieces of equipment.

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Logging cost; forest operations model; OpCost; fuel treatments; Forest Vegetation Simulator; BioSum

Introduction

Models have long been used in research and land management planning to understand and predict processes and systems of interest (Stage 1973; Vanclay & Skovsgaard 1997; Mitro 2001; McHugh 2006; Ackerman et al. 2014). The importance of using models has been just as crucial in understanding the financial aspects of timber harvest operations and hazardous fuel reduction (Matthews 1942; Bolding et al. 2003; Biesecker & Fight 2006). Reliable estimation of the costs of implementing harvests, or any kind of mechanical manipulation of forest vegetation, is important when prescribing, evaluating or comparing such forest operations (Matthews 1942; Pearce & Turner 1990; Røpke 2004). For example, accurate estimation of costs is needed to determine the extent to which anticipated sales of harvested material are likely to offset treatment expense, and to predict how much area can be treated for a given budget or level of subsidy. Whether forest treatments are motivated by forest products, forest health, fuels reduction, or any other goal, the cost of operations can be difficult to predict with confidence (Pearce & Turner 1990; Bolding et al. 2003; Jain et al. 2012). Reliable estimates of treatment costs provide land managers with information they need to understand the economic implications of alternative silvicultural prescriptions and implementation schedules to reduce fuels (Agee & Skinner 2005).

OpCost is a new forest operations cost model that builds on the Fuels Reduction Cost Simulator (Hartsough et al. 2006; Dykstra et al. 2009) and expands its functionality by adding new harvest systems and other enhancements, including newly published (since 2009) equipment production rate equations. Increasingly, OpCost is being used to simulate landscape level analysis to meet hazardous fuel reduction objectives and evaluate woody biomass utilization planning scenarios (Bell & Keefe 2014). In other subject areas of forestry, such as forest growth and yield modeling, model validation is considered an important process for informing model users about the performance and limitations of simulation models (Rykiel 1996; Weiskittel et al. 2011). Useful discussion of the advantages and disadvantages of alternative approaches to evaluating models is provided in Cawrse et al. (2010), Robinson and Froese (2004), Rykiel (1996), and Vanclay and Skovsgaard (1997). Despite the widespread use of predictive modeling in forest engineering and forest operations, and particularly the application of productive cycle time regression models developed using elemental time analysis (see e.g. Olsen & Kellogg 1983 for commonly used methods), there has been comparatively little use of formal model *validation* techniques to evaluate the quality of predictions that result from use of these models in practice (see e.g. Vanclay & Skovsgaard 1997; Kline 2011). The purpose of this paper is to more formally validate and evaluate the correspondence between predicted cost estimates generated through simulation using the OpCost logging cost model, which integrates several dozen such published equations, and estimates obtained from professional logging contractors for fuel reduction treatments with identical conditions. Conducting a formal evaluation of this sort for fuel treatments across a range of stand

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and site conditions regionally is both novel and of high importance, given that OpCost is now included in regional modeling efforts that are at times used to inform management and policy related to forest health, including recent deployment of OpCost as a component of the Bioregional Inventory Originated Simulation Under Management framework, or BioSum (Daugherty & Fried 2007; Barbour et al. 2008; Fried et al. 2016, 2017).

Like its predecessor, FRCS, OpCost is based on conventional, empirical cost estimation methods (Matthews 1942; Miyata 1980), but has been updated with recent, peer-reviewed production functions for many common harvesting systems. OpCost estimates costs associated with 11 harvesting systems as a function of stand characteristics, using descriptors of harvested trees derived from the output tables of the Forest Vegetation Simulator (FVS) model (Stage 1973; Dixon 2002) within the broader framework of landscape-level analysis of forest management and logistics in BioSum. U.S. Forest Inventory and Analysis (FIA) data are provided to FVS as input data. Stand growth based on those inventory data conditions are then projected over time using FVS. The resulting stand characteristics are interpreted within the BioSum framework (Fried et al. 2017). BioSum intermittently restructures and passes stand and site conditions to OpCost. OpCost then simulates harvesting for each stand prescription provided, and returns estimated treatment costs, often for several thousand stands on the landscape simultaneously (Fried et al. 2016, 2017). The resulting output is summarized by BioSum in the context of broader landscape forest management planning and logistics in ways that synthesize both forest health and renewable energy goals over large areas (Figure 1).

The BioSum framework thus enables landscape-scale analyses of silvicultural management alternatives and their ecological and economic outcomes in both time and space. At various stages, OpCost transforms stand prescription information into forms suitable as input to the many production and cost formulas referenced in Table 1 to simulate the costs of silvicultural activities. OpCost is designed to be used alternatively for individual stand treatment cost estimation by a model user, or to be run simultaneously for many stands within BioSum. With this latter approach, it is particularly important to represent the variability in costs for fuel treatments and associated woody biomass removals (e.g. chipping of small diameter stems removed in thinning operations). These vary widely on the landscape as a function of many factors, including stand productivity, species-specific defect, piece size, trees per acre being removed, and associated yarding distance (e.g. Keefe et al. 2014; Saralecos et al. 2015; Fried et al. 2016, 2017; Jacobson et al. 2016). These factors are known to affect how logging costs vary among regions, even within the Pacific Northwest USA (Dodson et al. 2015).

OpCost can operate in standalone mode to evaluate multiple management scenarios to estimate and facilitate comparison of economic implications of alternative treatments, including the present value of fuel reduction treatments conducted in the future. The model was developed to provide an open-source and transparent cost model to support both research and management with emphasis on forest health and bioenergy (Bell & Keefe 2014). This paper describes a formal validation of OpCost-simulated treatment costs expressed on a per unit area basis, and of the individual, equipment-specific production rates that influence those broader, system-level costs acros a range of fuel treatments. Because many contractors are reluctant to share detailed logging cost information and it is difficult to otherwise obtain consistent cost data over the wide range of stand density, slope, yarding distance, and other conditions that are provided to OpCost as input data when modeling forest health treatments, we instead developed a new, survey-based methodology that leveraged the expertise of professional logging contractors to evaluate the accuracy of OpCost predictions.

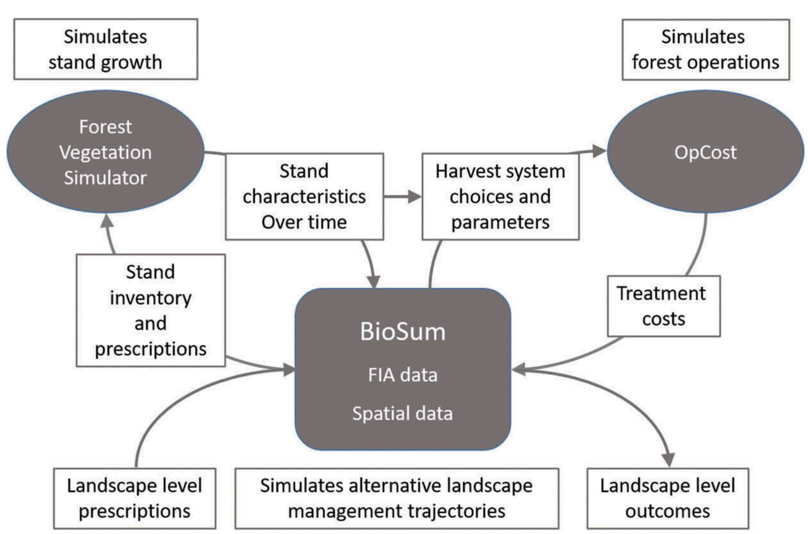

Figure 1. Relationship between OpCost and the Forest Vegetation Simulator (FVS) within the Bioregional Inventory Originated Simulation Under Management (BioSum) framework when conducting analysis of forest management scenarios over large, regional spatial extents (>1 million ac, or 404,685 ha) using the U.S. Forest Inventory and Analysis (FIA) database. Note that BioSum is an advanced simulation environment with many component models and this figure is intended only to highlight the role of OpCost within that framework.

Table 1. Sources of production and cost functions used in OpCost.

OpCost
Production equations
Chainsaw
Behjou & Majnounian (2009)
Klepac et al. (2011)
Ghaffariyan et al. (2012)
Hartsough & Xiaoshan (2001)
Lortz et al. (1997)
Kluender & Stokes (1996)
Visser & Spinelli (2012)
Wang et al. (2004)
Harvester
Acuna & Kellogg (2013)
Adebayo et al. (2007)
Berhongaray et al. (2013) Eliasson (1999)
Bolding et al. (2002)
Bolding & Lanford (2001)
Hiesl & Benjamin (2012)
Numinen et al. (2006)
Kärhä et al. (2004)
Klepac et al. (2006)
Klepac et al. (2011)
Keegan et al. (2002)
Drews et al. (2001)
Jiroušek et al. (2007)
Klepac et al. (2011)
Hiesl (2013)
Visser & Spinelli (2012)
Skidder
(Hiesl & Benjamin 2012)
Boswell (1998)
Ghaffariyan et al. (2012)
Keegan et al. (2002)
Kluender & Stokes (1996)
Bolding et al. (2002)
Wang et al. (2004)
Adebayo et al. (2007)
Wang et al. (2004)
Feller-buncher
Berhongaray et al. (2013)
Hartsough et al. (2001)
Boswell (2001)
(Kluender & Stokes 1996)
Hartsough et al. (1997)
Hartsough et al. (1997)
Dykstra (1976)
Spinelli et al. (2007)
Bolding et al. (2002 2001)
Kärhä et al. (2004)
Hiesl (2013)
Hiesl & Benjamin (2012)
Adebayo et al. (2007)
Wang et al. (2004)
Helicopter
Flatten (1991)
Dykstra (1976)
(Christian & Brackley 2007)
(Flatten 1991)
Forwarder
Acuna & Kellogg (2013)
Jiroušek et al. (2007)
Bolding (2001)
Bolding et al. (2002 2001)
Jiroušek et al. (2007)
Numinen et al. (2006)
Kluender & Stokes (1996)
Sirén & Aaltio (2003)
Dykstra (1976)
Drews et al. (2001)
Hiesl (2013)
Cable
Huyler & Ledoux (1997)
Drews et al. (2001)
Aubuchon (1982)
Dykstra (1976) Huyler & Ledoux (1997)

(*Continued*)

Table 1. (Continued).

OpCost
Boswell (2001)
LeDoux (1987)
Hartsough et al. (2001)
Hartsough & Xiaoshan (2001)
Chipper
Spinelli & Magagnotti (2014)
Bolding (2001)
Bolding & Lanford (2001)
Cuchet (2004)
Shovel
Sessions & Boston (2013)
Fisher (1986)
Wang & Haarlaa (2002)
Stroke-Boom Delimber
Hartsough et al. (2006)
Ghaffariyan et al. (2012)
Spinelli & Magagnotti (2010)
Hiesl (2013)

Materials and methods

After receiving permission from the Institutional Review Board at the University of Idaho for survey sampling involving human subjects (University of Idaho IRB protocol #16–1212), a validation survey was deployed using a mixed method sampling approach that incorporated both mail surveys and face-to-face contact at three regional logging conferences to sample logging contractors with expert knowledge of production rates and operational costs. Only contractors with at least 3 years of work experience were included in the study. According to the Bureau of Labor Statistics, there are approximately 740 logging workers in Idaho, 2230 in Washington and 3850 in Oregon as of 2013 (Bureau of Labor Statistics 2015). Of that number, we assumed that the number of individuals familiar with production rates and costs for all equipment in a given system, typically company owners or experienced supervisors at larger companies, was in the range of 1000–2000 individuals.

For the face-to-face component of the study, surveys were administered using a modified convenience sampling approach at three logging conferences in 2016: the Oregon Logging Conference in Eugene, OR; the Intermountain Logging Conference in Spokane, WA; and the Olympic Logging Conference in Victoria, BC. Convenience sampling is an effective method for surveying target populations of interest (Chein 1981; Singleton et al. 1993). Randomization can be introduced into sampling strategies for convenient populations by, for example, surveying at randomized times during events in order to reduce hidden biases (Tittle 1980; Dillman 2000). We modified this approach, as follows. After generating interest among potential respondents at each conference to consider completing a survey using the enticement of a chance to win a scale model of common logging equipment, we screened these individuals for experience with estimating logging costs, and drew our interview sample from the resulting group of interested and qualified participants.

Mail surveys were also sent to 248 contractors chosen randomly from lists of individuals registered with each state's professional logging association. Contractors were again screened using the same criteria. Using both methods (mail survey and face-to-face), a total of 132 completed surveys were received. Of these, 55 were excluded from the analysis reported in this paper because of missing information, unclear reporting of units or because the sample size was insufficient to evaluate logging systems that were not well represented in the surveys returned. For example, because a single survey was provided to each participant, several contractors who specialized primarily in one logging system (e.g. cable logging) received a survey designed for a different system (e.g. ground-based, cut-to-length) and only partially completed it. There was no defensible method for imputing missing values in logging system production rates or component cost estimates without confusing or adding bias to our model validation analysis. Consequently, if any component process (e.g. felling, skidding, processing or loading) was left blank or was unusable for other reasons, the entire survey was excluded from analysis. In this paper, data from 77 total completed surveys with high quality, complete estimates of individual equipment production rates and overall, system-level cost estimates for the four primary logging systems across the three state region were used in our analysis. This corresponds to approximately 20 surveys each for the four systems of interest. Assuming a population of contractors with logging cost expertise of approximately 1500 individuals regionally, the final sample size used in our study represents approximately 5.1% of the target population.

We relied on several techniques to reduce non-response, and the potential bias to which it could lead. These included personalized messages in the mail survey, use of the face-to-face survey approach at the three conference venues, and offering participants tokens of appreciation, which are known to reduce satisfice and non-response (Goyder 1985; Holbrook et al. 2003). The use of token prizes can also enhance the quality of data collected (Singleton et al. 1993; Holbrook et al. 2003; Aquilino 2009).

Surveys used in the study included 24 mock timber sale prospectuses representing a range of stand and site conditions for four different primary harvest systems deployed in forest management focused primarily on thinning or reduction of hazardous fuels in each of the three states. A total of 288 unique possible vignettes to be evaluated were developed and distributed as part of the analysis reported here. Use of this artificial timber sale prospectus method as the basis for estimating treatment costs was inspired by the success of this approach in construction surveys (Morrison 1984), as well as prior experience of a coauthor surveying wildland firefighters to estimate fireline production rates for quantitative modeling (Fried & Gilless 1989; Gilless & Fried 2000). The prospectus associated with each survey was tailored to conditions typical in the region where that contractor worked so that estimated production rates and costs could be used to distinguish fine resolution in model predictions across the ranges of several key input variables that vary considerably from coastal Oregon and Washington to dry sites in the Inland Northwest. Variability in local conditions, such as stem size (DBH), stand density, yarding distance, total stand volume, and biomass residue (logging slash) per acre are important factors affecting fuel reduction treatment costs and woody biomass logistics (Keefe et al. 2014; Jacobson et al. 2016). These predictors are important drivers of equipment-specific productive cycle times, and hence the treatment costs, for many of the time-and-motion studies referenced in Table 1. These equations work together in OpCost to simulate forest operations in landscape-level analyses.

For each mock timber sale prospectus, survey participants were asked to estimate the total treatment cost per acre, as well as the component production rates for each piece of equipment used in a given logging system, excluding move-in, move-out, and road development costs. Each participant developed estimates for a single prospectus corresponding to a single mock timber sale. Not all treatments were necessarily merchantable, as many included relatively small merchantable removal volumes typical of thinning operations. The majority of removals were less than 10 MBF ac^{-1}. Each mock prospectus included type of harvest system, yarding distance (ft), slope (%), harvested trees per acre by size class, net volume per acre (thousand board feet), gross volume per acre (thousand board feet), species composition as a percentage of stand basal area, the number of logs per acre, basal area per acre (sq. ft.), a hillshade map of the harvest unit, and total area of the harvest unit (acres). The format and range of stand conditions used to create mock prospectuses for the surveys were patterned from 38 operational timber sale prospectus documents obtained from the Idaho Department of Lands, Oregon Department of Forestry, and Washington Department of Natural Resources forestry divisions, and USDA Forest Service Regions 1 and 6. These operational prospectuses provided a basis for defining the ranges of variables considered as typical fuel treatments for the region and were generally partial harvests. Stand conditions for the mock prospectuses used in our surveys were generated using FVS, which ensured that OpCost predictions were based on conditions identical to those evaluated by logging contractors completing the surveys.

We assembled the survey-based stand treatment cost estimates and OpCost-simulated treatment costs for the identical stand conditions into a paired data set, and plotted all paired values. Quantile-quantile plots were used to evaluate the normality assumptions of linear regression (Singleton et al. 1993; Goodman 1996) and model residuals were plotted against OpCost predicted values. We then used model equivalence testing using the two one-sided t-test (TOST) to evaluate the similarity of OpCost predictions and survey-based estimates (Robinson & Froese 2004) for the same stand and site conditions. Equivalence testing provides a more conservative approach to validation of model predictions by shifting the burden of proof in statistical hypothesis testing. Rather than the usual statistical test indicating a lack of difference among two sample means, equivalence testing shifts the rejection region to provide evidence of similarity between observed and modeled (predicted) values (Robinson & Froese 2004). Equivalence testing has been used previously to validate that predicted tree diameter growth rates over time correspond well with actual measured growth rates observed in forest inventory data (Robinson & Froese 2004) and to evaluate GNSS-based predictions of loader swing cycle elements (Becker et al. 2017).

In this study, we adapted the approach to formally test whether fuel treatment cost predictions from OpCost were statistically similar to those obtained via expert assessments by logging contractors.

The collected surveys and OpCost estimates were analyzed using the *equivalence* package in R, which provides analytical methods for evaluating similarity of two samples (Robinson & Froese 2004; Robinson 2014). The null hypothesis tested was that the two populations of interest, in this case OpCost model predictions and contractor-provided estimates for the same stands and conditions, were *dissimilar*. We rejected dissimilarity with the alternative hypothesis that the populations were adequately similar, defined as having standardized differences between mean cost or production rate of no more than a specified magnitude. A two one-sided *t*-test (TOST) was used with a power of alpha = 0.1 and a predetermined acceptance threshold within 20% of the observed standard deviation. This type of statistical test was chosen because it provides a more conservative test for model evaluation than the more commonly used standard *t*-test, and the significance of the test is less affected by sample size (Robinson & Froese 2004). For each survey response, the cost of the complete harvesting system, represented as total treatment cost per unit area, was compared to the corresponding cost estimate generated through simulation using OpCost for the same harvesting systems and prospectus. This same analysis was then repeated again for the production rates of individual pieces of equipment, in order to better understand components of error in overall system-wide predictions of logging costs in fuel reduction operations.

Results

The null hypothesis of non-equivalence (dissimilarity) was rejected and the alternative was accepted when comparing OpCost predicted treatment costs per hectare and survey-based estimates for all four primary harvesting systems evaluated (cable manual whole-tree, ground-based manual whole-tree, ground-based cut-to-length, and ground-based mechanical whole-tree). Thus, for all four systems, OpCost predictions were statistically *similar* to survey-based estimates of total treatment cost per hectare provided by professional logging contractors across the range of stand and site characteristics considered in the three state region. Results from the two one-sided *t*-test (TOST) validation are shown in Table 2. For each system shown, the mean value reported is the mean difference between OpCost-predicted treatment cost per hectare and the corresponding, survey-based estimates from contractors. Estimates for ground-based mechanical whole-tree logging from OpCost had the greatest agreement with estimates provided by contractors, while they were least similar for cable-based manual whole-tree predictions.

Plots of OpCost-predicted treatment cost per acre and the corresponding survey-based estimates for the same stand conditions for each logging system are shown in Figure 2. Costs for ground-based manual whole-tree treatments tended to be over-predicted; predictions were greater than the survey estimates, showing evidence of a small positive bias. The same was true for cable manual whole-tree. However, correspondence improved at higher costs per hectare. Predictions for ground-based mechanical whole-tree were the least variable, judging by the extent to which observations depart from the 1:1 line and have the smallest standard deviation of OpCost and survey-based differences in Table 2 (71.2 \$US ac^{-1}). Errors associated with ground-based cut-to-length system predictions had high variability but did not show obvious prediction bias when evaluated graphically. Overall model residuals for all OpCost predictions and all survey estimates of treatment cost per unit area are shown in Figure 3.

Figures 2–5 show how OpCost-simulated production rates compare to logger estimated production rates for individual pieces of equipment operating within each harvest system. Using the same TOST validation method, the null hypothesis of dissimilarity was rejected for the predicted production rates of 5 out of 15 combinations of equipment and system, indicating accurate prediction of production rates for that subset. For the other 10 pieces of equipment, the null hypothesis could not be rejected, indicating that the model did not perform well. Dissimilarity between OpCost predicted and survey-generated individual equipment production rate was

Table 2. Two One-Sided *t-test* of the similarity between OpCost-predicted cost per unit area (in \$US) and an estimate for the same stand and site conditions provided by a professional logging contractor for each of the four systems. Mean values are the mean *difference* between predicted and survey-based estimates. For the mean and standard deviation (SD), values in parentheses are the cost in \$US ac^{-1} as reported in OpCost.

Metric	Cable manual WT	Ground-based manual WT
Dissimilarity	Rejected	Rejected
Mean	176 (71.2)	218.3 (88.3)
SD	564.6 (228.5)	311 (125.9)
Epsilon	530.2	295
Alpha	0.1	0.1
Cuttoff	2382	967.5
t statistic	1.4	2.8
Power	1	1
	Ground-based cut-to-length	Ground-based mechanical WT
Dissimilarity	Rejected	Rejected
Mean	79.9 (32.3)	112.5 (45.5)
SD	344.9 (139.6)	176.6 (71.5)
Epsilon	411.3	188.9
Alpha	0.1	0.1
Cuttoff	1464	642.1
t statistic	1	2.6
Power	1	1

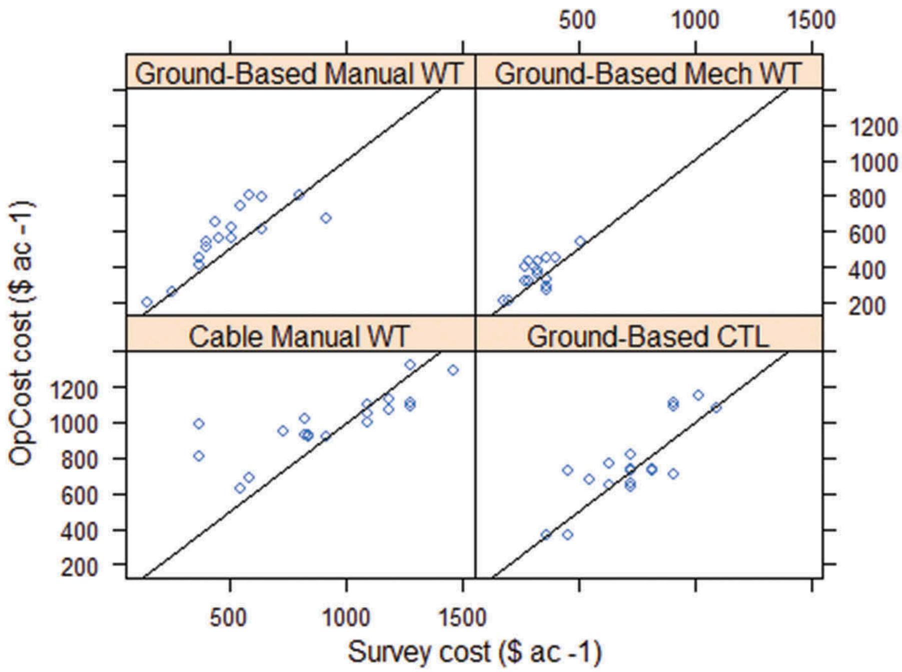

Figure 2. Scatterplot of OpCost estimated harvest cost vs. logger estimated harvest costs for all timber sale prospectus vignettes in each harvest system.

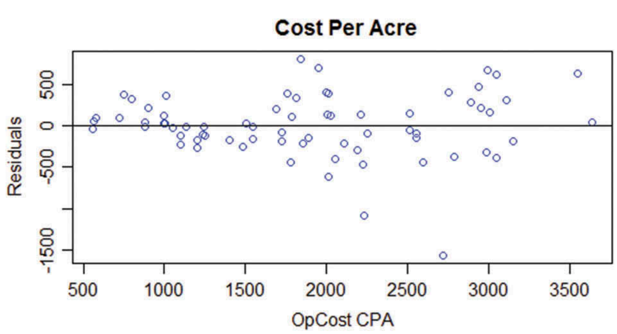

Figure 3. Model residuals vs fitted values for all predicted costs per unit area, including all harvest systems evaluated in this study. Fitted values on the X-axis are the OpCost-simulated costs per unit area for each timber sale prospectus vignette; residuals are the difference between costs per unit area (ac) estimated by contractors and the corresponding treatment cost predicted using OpCost.

rejected for sawyers, processors, and loaders operating in a cable-based manual whole-tree system, indicating good correspondence between model predicted production rates and estimates provided by professional contractors for those types of equipment. Dissimilarity was also rejected for sawyers and skidders operating in the ground-based manual whole-tree system, as well as for feller- bunchers operating in the ground-based mechanical whole-tree system.

The null hypothesis of dissimilarity was *not* rejected for the yarder and loader in the cable manual whole-tree system; for the processor and loader operating in a ground-based manual whole-tree system; for harvesters, forwarders, and loaders operating under a ground-based cut-to-length system; or for skidders, loader, and the processor operating in a ground-based mechanical whole-tree system (Table 3). Analysis of the OpCost predictions and survey-based estimates in Figures 4–7 shows noticeable discrepancies in predicted production rates for individual equipment within some of these systems, particularly the cut-to-length.

Discussion

The equations used in StHarvest (Hartsough et al. 2001), a progenitor to FRCS (Hartsough et al. 2006) and OpCost have been widely used in a variety of studies to prioritize fuels reduction treatments (Bolding et al. 2003; Waltz et al. 2014) and to predict biomass harvesting costs at regional to national scales (Dykstra et al. 2009). When models are used to make predictions with policy implications, it is important to evaluate the behavior of the models used and to validate predictions against independent observations. Expert opinion surveys are useful as a proxy for observed rates when empirical measurement proves impractical or infeasible (Fried & Gilless 1989). Professional contract loggers are the pre-eminent experts capable of estimating costs for the broad range of specific stand conditions and harvest systems in the Pacific Northwest, and their cooperation enabled development of this independent validation data set. The comparisons between OpCost predictions and expert opinion are useful for informing model users about the accuracy of predicted fuel treatment costs and how these vary among harvest systems and stand conditions.

OpCost currently includes six other harvesting systems that were not evaluated in this study due to logistical constraints and our decision to focus on validating the most commonly used systems. This evaluation of OpCost produced information about model performance with respect to both costs associated with complete harvest systems and time requirements for individual equipment components of

Table 3. Two One-Sided t-test (TOST) evaluating similarity between OpCost predicted production rate in MBF hr^{-1} and the corresponding rate estimated by contractors for treatments with the same stand and site conditions. The corresponding rate in m^3 SMH^{-1} is shown in parentheses for the mean and standard deviation (SD).

	Cable manual WT			
Metric	Sawyer	Yarder	Processor	Loader
Dissimilarity	Rejected	Not rejected	Rejected	Not rejected
Mean	−0.16 (−1.0)	−0.52 (−3.34)	0.2 (1.3)	2.1 (13.5)
SD	2.3 (14.8)	1.6 (10.3)	0.8 (5.1)	0.96 (6.2)
Epsilon	0.5	0.5	0.7	0.25
Alpha	0.1	0.1	0.1	0.1
Cutoff	0.8	0.7	1.3	0.23
t statistic	−0.26	−1.1	0.9	9.9
Power	0.58	0.5	0.8	0.18
	Ground-based mechanical WT			
	Fellerbuncher	Skidder	Processor	Loader
Dissimilarity	Rejected	Not rejected	Not rejected	Not rejected
Mean	0.008 (0.05)	−0.14 (−0.9)	−0.22 (−1.4)	1.7 (10.9)
SD	0.36 (2.3)	0.52 (3.3)	0.23 (1.5)	0.83 (5.3)
Epsilon	0.33	0.52	0.12	0.25
Alpha	0.1	0.1	0.1	0.1
Cutoff	0.3	0.79	0.14	0.2
t statistic	0.08	−1.1	−3.7	8.13
Power	0.24	0.56	0.11	0.17
	Ground-based manual WT			
	Sawyer	Skidder	Processor	Loader
Dissimilarity	Rejected	Rejected	Not rejected	Not rejected
Mean	0.7 (4.5)	0.07 (0.45)	0.44 (2.8)	1.7 (10.9)
SD	1.5 (9.6)	0.5 (3.2)	0.72 (4.6)	0.8 (5.1)
Epsilon	0.8	0.47	0.9	0.25
Alpha	0.1	0.1	0.1	0.05
Cutoff	2	0.67	2.3	0.1
t statistic	1.8	0.61	2.54	8.13
Power	0.94	0.49	0.97	0.08
	Ground-based cut-to-length			
	Harvester	Forwarder	Loader	
Dissimilarity	Not rejected	Not rejected	Not rejected	
Mean	−0.49 (−3.1)	−0.3 (−1.9)	−0.29 (−1.9)	
SD	0.8 (5.1)	0.9 (5.8)	0.5 (3.2)	
Epsilon	0.24	0.4	0.15	
Alpha	0.1	0.1	0.1	
Cutoff	0.19	0.49	0.15	
t statistic	−2.2	−1.31	−2.2	
Power	0.15	0.37	0.12	

those. The latter provides additional insight into which kinds of equipment may be the greatest potential sources of error and are deserving of additional new model development or calibration.

The OpCost model performed reasonably well for predicting overall treatment costs for the four complete harvesting systems evaluated in this study over a broad range of topographic and stand conditions representative of conventional fuel reduction treatments deployed in the northwestern United States. The null hypothesis that OpCost-simulated per-acre costs and contractor-provided estimates for the same stands were dissimilar was rejected in each case. However, users of OpCost should note where the model tends to predict the production rates for individual component equipment within each system poorly. This likely reflects biases associated with individual time studies used to develop OpCost, which have often been developed under fairly narrow, localized stand conditions. For cable manual whole-tree harvesting, many of the cost estimates generated by OpCost were higher than the expert estimates when those estimates are low (less expensive treatments). Results for the individual equipment components that comprise that system suggest that OpCost may also underestimate sawyer production rate, which could account for some of the overstatement of costs. OpCost also markedly over-predicted costs for the ground-based manual whole-tree system over the full range of treatment costs by 27%. However, there appears to be some over-prediction of skidding and sawing costs and underestimation of production rates for stands with higher overall harvest costs (15% and 40% respectively). Estimates for the ground-based mechanical whole-tree and ground-based cut-to-length systems do not strongly over- or under-predict, but the ground-based cut-to-length system does have noticeably more variability in the prediction error than the ground-based mechanical whole-tree system. However, the lower variability shown with the ground-based mechanical whole-tree system could be partially attributed to the lower overall costs for that system. Because OpCost's system-level cost estimate is an accumulation of the time estimates and cost rates of the equipment involved, some of which may be over-

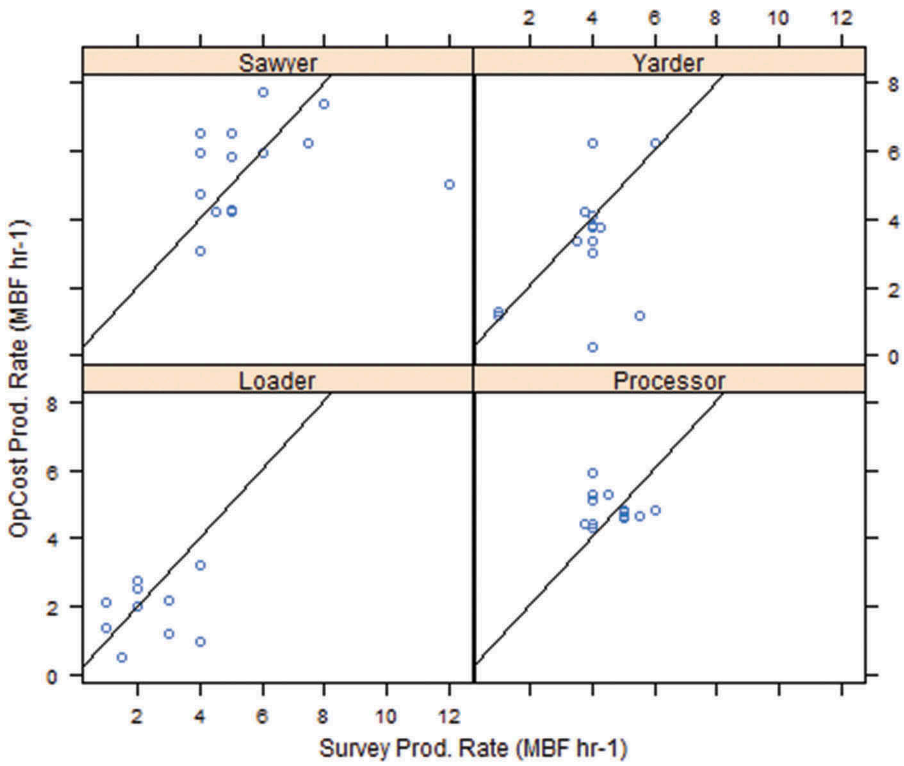

Figure 4. Scatterplot of OpCost estimated production rates vs. logger estimated production rates for all timber sale prospectus vignettes by equipment type within the cable-based manual whole tree system.

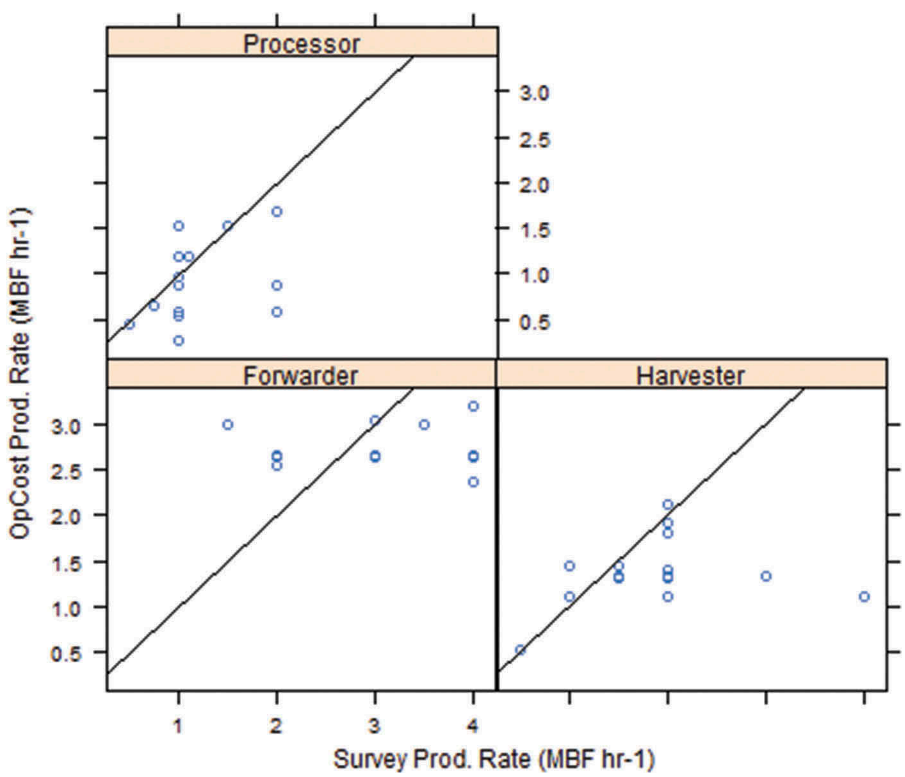

Figure 5. Scatterplot of OpCost estimated production rates vs. logger estimated production rates for timber sale prospectus vignettes by equipment type within the ground-based mechanical cut-to-length system.

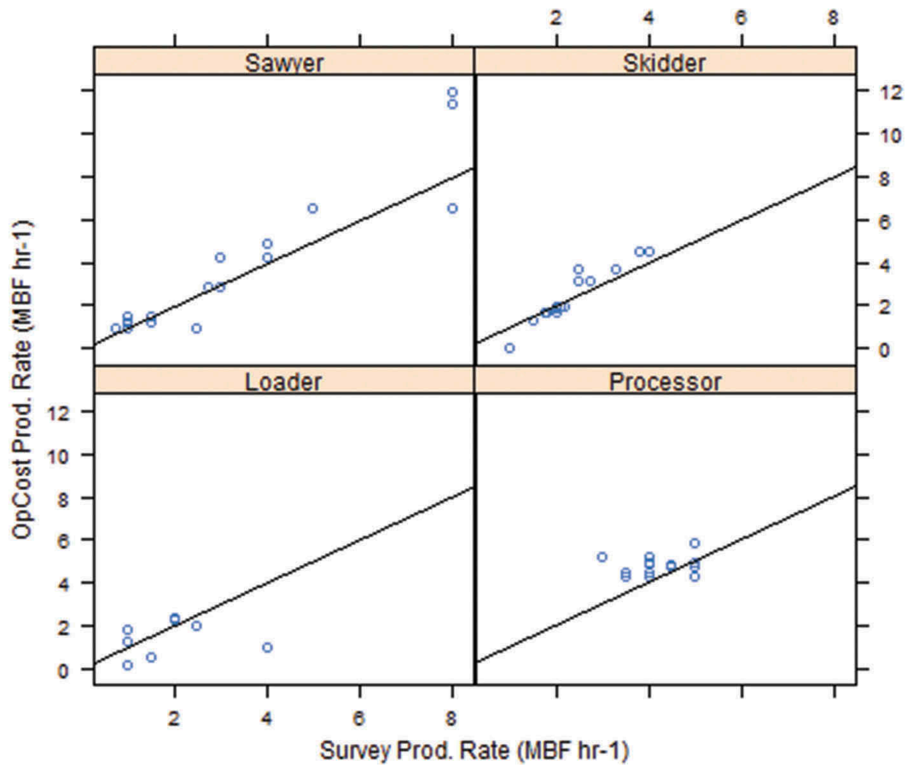

Figure 6. Scatterplot of OpCost estimated production rates vs. logger estimated production rates for timber sale prospectus vignettes by equipment type within the ground-based manual whole tree system.

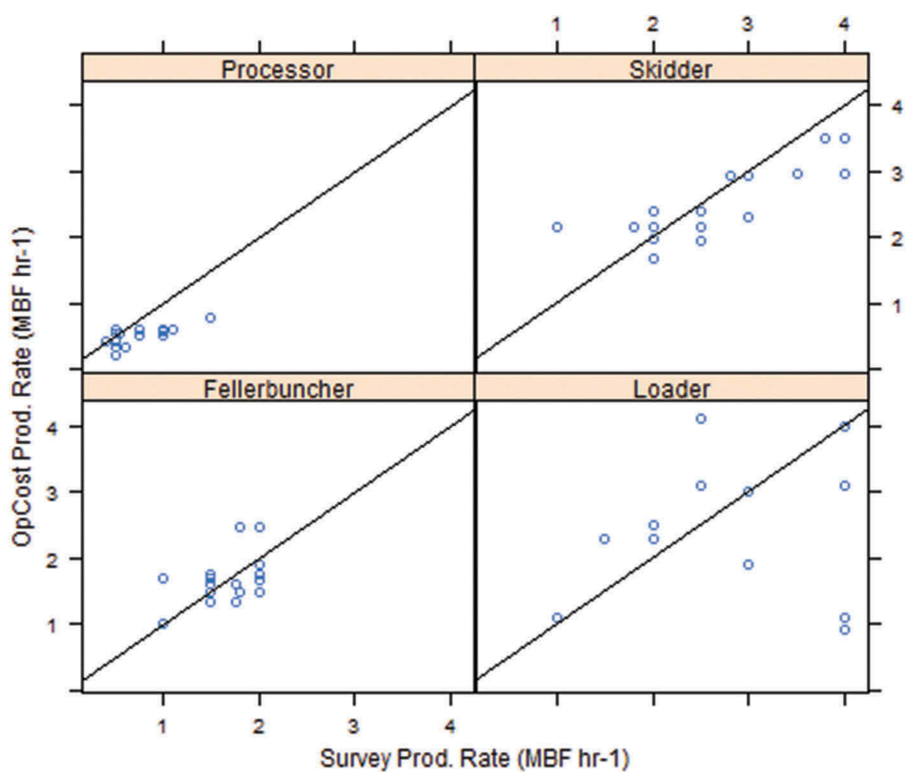

Figure 7. Scatterplot of OpCost estimated production rates vs. logger estimated production rates for all timber sale prospectus vignettes by equipment type within the ground-based mechanical whole tree system.

or under-predicted, the system cost estimates can show less variation than is seen for the individual equipment types owing to compensating errors.

In addition to understanding OpCost performance relative to expert opinion, users must be aware of inherent limitations. For example, given that production rates can fluctuate greatly within a harvesting unit, and that OpCost does not account for within-unit variability in conditions that could materially affect production rates, users assessing actual or hypothetical fuel treatments on a specific piece of ground are advised to be selective about linking OpCost to appropriately scaled stand inventory data. Large, heterogeneous units are better partitioned into smaller, more homogeneous subunits for analysis with OpCost if inventory data are available for each subunit. This is especially true when modeling treatments in areas with mixed topography including both ground-based and cable operations. These and several key model assumptions available in forthcoming documentation of the development of OpCost are important to consider when using the model for research or to support operational planning. Users should also understand that actual costs may depart from OpCost predictions if OpCost's inputs don't accurately account for real world conditions.

We believe that when OpCost is implemented with representative inputs at the stand level or for whole landscapes (e.g. for BioSum analyses), it will prove useful to researchers, landowners, and managers because it allows automation of treatment cost estimation in a way that is linked seamlessly with forest inventory data and stand growth and yield. Integration with outputs from the Forest Vegetation Simulator (FVS), e.g. via the summary metrics generated by BioSum, significantly enhances the range of future simulation analyses that can reflect forest succession, management and disturbance over decades, as well as a conscious strategy to implement an intentional sequence of silvicultural activities, for example, to achieve forest restoration through sustainable management (e.g. Fried et al. 2016), or to simulate impacts of management policies on bioenergy markets. Although additional evaluation will be beneficial for the harvest systems not included in this study, as well as any future systems that may be added, these results confirm a reasonable correspondence between treatment costs predicted by OpCost and those estimated by professional contractors.

Conclusion

Formal comparison of the outputs from the OpCost model to expert estimates provided by professional logging contractors provide support for the conclusion that total fuel treatment cost predictions from OpCost are sufficiently accurate for the kinds of landscape-scale applications for which the model is currently being used within BioSum. Overall OpCost model predictions were typically within 20% of costs predicted by experts for the four common harvesting systems we evaluated, across a range of stand and site conditions that are representative of expected variability in fuel treatments in the Pacific Northwest United States, particularly on state and federal lands. As noted, several equipment-specific models that make up some systems did not predict production rates well across conditions outside those for which they were originally developed. Consequently, model users should be cautious when using individual component models to predict piecewise costs (e.g. only forwarding costs in a CTL system) when using OpCost or BioSum for more localized or customized analyses. These submodels should also be targeted for future model improvement. In general, referring to Figures 4–7 in this article in order to evaluate equipment-specific models is the easiest way to gauge the expected quality of individual stand predictions when using OpCost for specialized projects.

Validation is an important step in many fields of research that utilize simulation modeling. It provides model users with an understanding of the strengths and weaknesses of the analytical tools they use. Model validation has been deployed infrequently in the analysis of production and costs in forest operations and forest engineering. We have shown that validation using equivalence testing, particularly when coupled with survey sampling of professional logging contractors, provides a useful approach for evaluating logging cost models. Consistently developed logging cost data from a range of operational conditions is often difficult to obtain due to variability in methods used for cost-accounting by contractors and an understandable reluctance to publicly share sensitive information about forest business transactions. Using simulated stand conditions coupled with survey sampling proved to be a useful technique for standardizing logging cost information received from contractors. Doing so allowed us to validate OpCost across the range of stand and site conditions it is currently being used tomake predictions for. Further, this method makes it possible to draw on the expertise of many contractors while still retaining a high level of consistency in the assumptions and methods used to estimate treatment costs.

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