Development and Validation of the OpCost Forest Operations Cost Model

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Authorization to Submit Thesis

This thesis of Conor K. Bell, submitted for the degree of Master of Science with a major in Natural Resources and titled "Development and Validation of the OpCost Forest Operations Cost Model," has been reviewed in final form. Permission, as indicated by the signatures and dates given below, is now granted to submit final copies to the College of Graduate Studies for approval.

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Abstract

OpCost is an open-source forest operations cost simulator written in the R statistical programming language. OpCost is an updated version of an earlier model, the Fuel Reduction Cost Simulator (FRCS), with increased functionality. OpCost also has faster processing speed when used within the landscape-scale analytical framework, Bioregional Inventory Originated Under Management (BioSum). In this thesis, after providing a brief background on cost modeling in operational forestry, I describe the development and structure of OpCost in Chapter 2, which is subsequently being published as a General Technical Report by the USDA Forest Service Pacific Northwest Research Station. In Chapter 3, I describe a study conducted to validate OpCost predictions using an independent data set, something which has not been common in the fields of forest operations or forest engineering. In order to validate model predictions, I used a mixed method survey approach to sample professional logging contractor estimates of logging costs at each of three regional logging conferences in Idaho, Washington and Oregon in 2016. Stand and site conditions for timber sales with a range of pre-treatment conditions were generated using the Forest Vegetation Simulator model coupled with GIS. This approach made it possible to obtain both OpCost-generated predictions of fuel reduction treatment costs, and contractor estimated costs for areas with identical conditions. OpCost predictions for total, system-wide treatment cost, were not different from contractor estimates when compared using equivalence testing. However, the production rates of individual pieces of equipment estimated by contractors differed from those predicted by OpCost. Our approach to model validation using contractor surveys was novel and useful because it facilitated standardized conditions provided as input to both the contractors and the model. Fuel treatment cost estimation is critical for determining the cost effectiveness of management decisions at the wildland urban interface (WUI) and beyond. This work will help to advance landscape-scale analysis of the cost-effectiveness of fuel treatments, guiding researchers and managers in better understanding the long-term implications of their management decisions.

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Chapter 1:

Operational Planning and Cost Estimation

Having accurate cost estimates of forest operations is essential for evaluating the economic feasibility of forest management alternatives. The need for accurate cost estimates becomes even greater when planning forest restoration activities as the cost of the operations frequently exceeds the revenue from recovered material. The Fuels Reduction Cost Simulator (FRCS, Hartsough, Fight, & Noordijk, 2006) sought to address this need with a macro-driven, multi-sheet Excel spreadsheet tool into which users could enter parameters involving a stand and the material to be harvested as part of fuel treatment operations. In FRCS, and in OpCost, a user chooses a harvest system appropriate for a given site and stand conditions, specifies the “cut list” that results from applying a silvicultural prescription designed to reduce fuel loadings, and obtains estimated costs associated with implementation of that prescription. As interest grew in obtaining such estimates for large numbers of stands treated via a range of alternative prescriptions simulated on the landscape simultaneously, as implemented in the BioSum model (Fried et al 2016), the inherent limitations of the spreadsheet-based paradigm for simulating operational costs became evident. Forest engineers at the University of Idaho, with support from the Joint Fire Sciences Program, undertook a complete revamp of current harvesting cost models. The products of their efforts include the OpCost forest operations cost model, programmed in R, and a validation study that compared OpCost estimates with expert judgment collected via a formally designed survey of logging professionals (Bell et al. 2016). In addition to updating currently available production functions and cost estimates based on recent literature, OpCost includes some additional harvest system capabilities, such as simulation of shovel logging, and has improved methods for interfacing with BioSum.

OpCost incorporates production rates from over 85 studies, many with a vintage more recent than the last version of FRCS, released in 2009, of both manual and mechanized operational systems. One edition, OpCost BioSum Edition (BE), is distributed with the BioSum software and implemented as a callable code package running under the R interpreter. OpCost BE is tightly integrated with BioSum to estimate the costs for modeled forest harvest operations simulated under that analysis framework. The other edition, OpCost Stand-alone Edition (SE), can be run directly from the R development environment (R Development Core Team, 2016). OpCost is driven by the same variables used as inputs to its predecessor, FRCS. For trees simulated as harvested, 24 variables account for average volume per tree, number of trees harvested per acre, hardwood fraction, residue fraction and wood density for each of three user-defined tree size classes, along with trees per acre and average tree volume of small ("brush cut" size, in FRCS parlance) trees that are cut but not utilized. Other inputs include slope and average distance to the nearest landing.

OpCost greatly streamlines workflow of a batch operation relative to FRCS by eliminating the need to export data to Microsoft Excel as an intermediate step prior to cost estimation. OpCost is also designed to operate in batch mode, but reads inputs from and writes outputs to MS Access database tables, making it equally easy for users to estimate costs for one stand and treatment or thousands of stands and dozens of treatment alternatives. The integration of OpCost with BioSum produces cost estimates for each analyst-specified combination of silvicultural prescription and harvest system on each inventory plot modeled in BioSum. This facilitates estimates of cost-effectiveness for a wide range of fuel treatments on managed forests in the West. The system can also be used to estimate harvest costs for implementing any silvicultural prescription, not just those intended for hazardous fuel reductions.

Models have long been used in research and land management planning to understand and predict processes and systems of interest (McHugh, 2006; Mitro, 2001; Vanclay & Skovsgaard, 1997). The importance of using models has been just as crucial in understanding the financial aspects of timber harvest operations and hazardous fuel reduction (Biesecker & Fight, 2006; M. C. Bolding, Lanford, & Kellogg, 2003; D. Matthews, 1942). Reliable estimates 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 (D. M. Matthews, 1942; Pearce & Turner, 1990; Røpke, 2004), for example determining the extent to which anticipated sales of harvested material are likely to offset operations costs, 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 (M. C. Bolding et al., 2003; Jain et al., 2012; Pearce & Turner, 1990). Reliable estimates of treatment cost provides land managers with information they need to understand the economic implications of alternative silvicultural prescriptions and implementation schedules (Agee & Skinner, 2005).

A new forest operations cost model was developed that builds on the Fuels Reduction Cost Simulator (D. Dykstra, Hartsough, & Stokes, 2009; B. Hartsough, Fight, & Noordijk, 2006) and expands its functionality by adding new harvest systems and other enhancements, including newly published (since 2009) equipment production rate equations. As in other areas of forestry, such as forest growth and yield modeling, model validation is an important process for informing model users about the performance and limitations of simulation models (Rykiel, 1996; Weiskittel, Hann, Jr, & Vanclay, 2011). Useful discussion of the advantages and disadvantages of alternative approaches to evaluating models is provided in Cawrse et al. (2010), Robinson & Froese (2004), Rykiel (1996), and Vanclay & Skovsgaard (1997). The purpose of this validation is to evaluate the correspondence between the cost estimates generated by OpCost and estimates obtained from logging professionals for hypothetical operations. Conducting a formal evaluation is somewhat novel given that model validation has not been deployed widely in forest operations (Kline, 2011; Vanclay & Skovsgaard, 1997).

Like its predecessor, FRCS, OpCost is based on conventional, empirical cost control methods as described in Matthews (1942), 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 CUTLIST table output of the Forest Vegetation Simulator (FVS) model (Dixon, 2002; Stage, 1973) as input. OpCost can also evaluate multiple management scenarios to estimate and facilitate comparison of economic implications of alternative treatments, including the present value of treatments conducted in the future. OpCost was developed to provide a user friendly, open-source, and transparent forest operations cost model to support both research and management (Bell et al. 2016). This paper describes a formal validation of OpCost with respect to both harvest systems (in terms of operations cost) and the individual equipment types that collectively comprise each harvest system.

Chapter 2:

OpCost: an Open-Source System for Estimating Costs of Stand-Level Forest Operations

Abstract

This report describes and documents the OpCost forest operations cost model, a key component of the BioSum analysis framework. OpCost is available in two editions: as a callable executable for use with BioSum, and in a stand-alone edition that can be run directly from R. OpCost model logic and assumptions for this open-source tool are explained, references to the literature used for all of the sub=models included in OpCost are provided, and guidance is offered on how to change the default hourly machine rates associated with overall logging cost calculations. OpCost enhancements such as cost component breakout, and identifying the least cost harvest system, are also described and explained.

Introduction

Estimating costs of forest operations is essential for evaluating the economic feasibility of forest management alternatives, especially those involving partial harvest conducted as a component of forest restoration, where costs may be a large fraction of, or exceed, revenues from sales of harvested wood. The Fuels Reduction Cost Simulator (FRCS) (Fight et al. 2006), the development of which began over two decades ago, sought to address this need with a multi-sheet Excel®[1] spreadsheet tool into which users could enter parameters associated with stand conditions and the material to be harvested as part of fuel treatment operations. In FRCS, and in OpCost, the user chooses a harvest system appropriate for a given site and stand conditions, specifies the "cut list" that results from applying a silvicultural prescription designed to reduce fuel loadings, and obtains estimated costs associated with implementation of that prescription. As interest grew in obtaining treatment cost estimates for large numbers of stands treated via a range of alternative prescriptions simulated on the landscape simultaneously, as implemented in the BioSum model (Fried et al. 2016) and other approaches to modeling landscape-scale operational logistics (Jacobson et al. 2016), the inherent limitations of the spreadsheet-based paradigm for simulating operational costs became evident. Operations foresters at the University of Idaho, with support from the Joint Fire Sciences Program, undertook a revision and restructuring of the FRCS model. The products of their efforts include the OpCost forest operations cost model, programmed in R, and a validation study that compared OpCost estimates with expert judgments collected via a formally designed survey of logging professionals (Bell et al. 2017). In addition to updating currently available production functions and cost estimates based on recent literature, OpCost includes some additional harvest system capabilities, such as simulation of shovel logging, and provides a more reliable interface to BioSum.

OpCost incorporates production rates from over 85 studies, many with a vintage more recent than the last version of FRCS, released in 2009, of both manual and mechanized operational systems. One edition of the model, OpCost BioSum Edition (BE), is distributed with the BioSum software. OpCost BE is a callable code package, running under R (R Development Core Team 2016), that tightly integrates with BioSum to estimate the costs for modeled forest harvest operations simulated under that analysis framework. The other edition, OpCost Stand-alone Edition (SE), can be run directly from the R development environment. OpCost is driven by essentially the same variables used as inputs to its predecessor, FRCS. For trees simulated as harvested, 35 variables account for average volume per tree, number of trees harvested per acre, hardwood fraction, merchantable volume as a percentage of total volume and wood density for each of three user-defined tree size classes, along with trees per acre and average tree volume of small ("brush cut" size, in FRCS parlance) trees that are cut but not utilized. Other inputs include slope and average distance to the nearest landing and, for small and large log trees, the percentage of wood volume transported to the landing that will be chipped owing to its derivation from trees of submerchantable size or noncommercial species. Average travel time, in hours, required to move-in a harvest system equipment component (e.g., a skidder) to the harvest site and operation size, in acres, are required to estimate move-in costs on a per acre basis.

OpCost greatly streamlines workflow of a batch operation relative to FRCS by eliminating the need to export data to Microsoft Excel as an intermediate step prior to cost estimation. OpCost is also designed to operate in batch mode, but reads inputs from and writes outputs to MS Access database tables, making it equally easy for users to estimate costs for one stand and treatment or thousands of stands and dozens of treatment alternatives. The integration of OpCost with BioSum produces cost estimates for each analyst specified combination of silvicultural prescription and harvest system on each inventory plot modeled in BioSum. This facilitates estimates of cost-effectiveness for the wide range of fuel treatments on managed forests in the Western United States (see, e.g., Jain et al. 2012). The system can also estimate harvest costs for implementing any silvicultural prescription, not just those intended to reduce hazardous fuels.

OpCost Framework: Overview

Production functions in OpCost use, as inputs, the estimated amount of removed or altered material within forest stands based on summary metrics from simulated silvicultural prescriptions that generate a "cut list" in the FVS (Forest Vegetation Simulator) (Dixon 2002) format. These predict, on a per-acre basis, the time and expense required to harvest and process wood volume. In essence, OpCost is an equation filtering and aggregation engine that, considering the specifics of a stand, silvicultural treatment to be modeled, and harvest system to be implemented, applies several possible equations extracted from peer-reviewed forest operations literature. These are typically based on past elemental time analysis and work sampling studies that are identified as applicable to the stand and site under consideration; OpCost computes the average of the predictions of all applicable equations. By using the regression equations from descriptive studies, OpCost can predict the production rates of the equipment within certain conditions. Applicability is determined by whether an equation is eliminated from consideration by "rejection" criteria that differ among equations for a given harvesting, extraction, or processing machine. Examples of rejection criteria, which are evaluated for each operation based on whether or not the OpCost inputs fall within the acceptable range for an equation, include slope, average volume per tree, average distance to landing, whether hardwoods are part of the harvest, average tree diameter, average tree weight, and harvested trees per acre. Non-rejected equations for each machine used in a harvest system advance to the next computation phase. The rejection criteria are based on the range of data over which original studies were evaluated, in order to avoid extrapolation of production or cost functions beyond the range of their source data and intended application.

Estimating machine time required

A harvest system can be thought of as a collection of the equipment, or machines, and labor required to implement operations under that system. For example, a Cable Manual Whole-tree system typically operates on steep slopes and, after manual tree felling by a sawyer, brings entire trees, including bole, branches and top (as opposed to previously-bucked logs) to the landing using a yarder. At the landing, whole trees are processed into merchantable logs and nonmerchantable residues with a processor, which may be either a stroke-boom delimber or danglehead processor. Logs are then loaded onto log trucks with a loader and residues are chipped and blown into a chip van. Thus, this system involves five machines: manual felling (sawyer with a chainsaw), yarder, processor, loader, and chipper, each of which may have up to a dozen or more published equations that could be used to predict the time required per unit of trees or volume handled. Given the diversity of study purposes and locales behind the published equations, and differences in the factors affecting costs for different machines, tree units differ among machines and among studies. Wood characteristics tracked by the model may be expressed on a volume or mass basis, depending on the relevant production function and study. Volumes may be expressed in cubic feet, board feet, cords or cubic meters, and mass values may be in pounds or kilograms. Times are summed across size classes, and these sums are then combined into the mean time in hours per acre.

Estimating machine cost

Once total machine working time has been adjusted into hours per acre, machine cost per acre is computed as the product of hours and machine cost rates, which are based on conventional cost control processes (Matthews 1942). Calculations occur in productive machine hours (PMH) and following convention in forest operations studies, a utilization rate is assigned to distinguish between production and delay time. Because OpCost generates estimates at a stand level, without regard to stand location, it cannot assign location-specific move-in costs associated with each machine's use. However, when using OpCost within a BioSum analysis, per acre move-in costs can be accounted for based on travel time to wood processing facilities (a parameter calculated as part of the BioSum workflow and a viable proxy for move-in time) and assumed stand area undergoing treatment. Move-in costs could also be affected by the locations of scheduled work in a particular year; however, this level of detail is beyond the scope of OpCost and BioSum and is not addressed. Wherever available, machine rates include fixed and variable costs associated with owning and operating the equipment. These have been updated with current estimates (Dodson et al. 2015). Default machine cost rates, developed for the Pacific Northwest region, are supplied in the OpCost code, but can be changed by the user, if desired and necessary, via a straightforward text edit to the open source model code (for OpCost BE) or to the appropriate input table (for OpCost SE).

Estimating harvest system cost

After machine cost estimates are complete, harvest cost per acre can be calculated as the sum of each of the predicted machine-specific treatment costs associated with the harvest system working in the BioSum-supplied site and stand conditions. For the cable manual whole-tree system example, this would be the sum of treatment costs per acre for sawyer, yarder and carriage combination, processor, loader, and chipper. Treatment cost accounts for both the machine rates and the production rates for each piece of equipment. Production rates are typically expressed in tons per PMH or MBF per PMH and provide predictions of the total treatment time required by each piece of equipment to treat volume removed per acre. See, e.g. Keefe et al. (2014) for further description of the relationship between machine rates, production rates, and treatment costs. Move-in cost, derived from the number of machines transported to the harvest site and assumptions that account for delays in setting up equipment, when applicable, is added to obtain the final harvest cost reported in the table OpCost_Output. That table also contains calculated move-in cost in a separate column to better inform the analyst wishing to consider, for example, savings that might accrue from consolidating forest operations.

Enhancements

A significant enhancement compared to FRCS is the simultaneous estimation of costs for multiple, potentially more cost-efficient harvest systems. These estimates can be compared to the costs of the analyst- specified harvest system, replacing them if desired. By default, cost estimates for the lowest cost harvest system are output to a table called "OpCost_Ideal_Output." Users wishing to prevent the creation of this table, thus slightly shortening execution time, can change the "1" to a "0" in the following OpCost statement: idealTable←1 (currently line 20 in version 8.7.9) of the executable code.

Another new feature is the reporting of chipping costs in a separate column in both the OpCost_Output and OpCost_ Ideal_Output tables. This could be useful when considering alternative approaches to disposal of harvest residues, as when a treatment leaves residues at the landing for collection as firewood or later burning— chipping cost might then be deducted from the harvest cost.

How it works- in detail

This section describes OpCost processing in greater detail, including the specific inputs and intermediate processing steps. This information is current as of version 8.7.9.

OpCost predicts operations costs for 11 harvest systems. Each system can be thought of as an integrated sequence of activities utilizing several pieces of equipment, operating in a coordinated fashion, to move wood from trees to trucks, while accomplishing management objectives. For example, a harvest system may be used to transform a forest stand in terms of its density, tree species and size distribution, surface vegetation and fuels, and emergent properties such as forest health, resistance to fire, and overall resilience that derive from these. In addition to differences in how harvested material is felled and transported, harvest systems differ in the materials that are collected for utilization. OpCost provides for five harvest system categories to reflect these differences when estimating operations costs (table 1). The 11 systems included in OpCost (table 2) cover nearly all forest management activities that involve mechanical fuel treatment and other harvest. To estimate the cost of applying these systems to implement particular prescriptions on specific stands, OpCost relies on 124 equations extracted from 82 published articles (table 3) covering all 11 machine types used in these 11 harvest systems. For each equipment type, the available equations differ in the inputs that are required, so the “independent variables” column in table 3 is an exhaustive list of attributes used by any of the equations in the equipment category. The meaning of most of these attributes is straightforward. Piece volume is average volume per tree; total volume is volume per acre. Depending on the equation, species group is ultimately either a binary descriptor indicating whether hardwoods comprise more than 1 percent of the harvested material or the percentage of volume that is in hardwoods.

Inputs

BioSum initiates an instance of R, passing to it the OpCost BE filename and the name of an Access file that contains all input data in a table named opcost_input. This table consists of 35 attributes per stand (table 4). In general, but with a few exceptions for size classes, where some are not needed, there is a quintet of harvested tree descriptors for each of four size classes defined by the user in BioSum, plus a few site descriptors. Note that the size class definitions themselves (in terms of minimum and maximum diameter at breast height [d.b.h.]) are not passed to, or needed by, OpCost. The four size classes are brush cut (BC), chip trees (CT), small log trees (SLT) and large log trees (LLT). Each of these size classes is determined by the analyst. The BC trees are harvested but not utilized, so OpCost accounts only for the costs of their felling. The CT boles are assumed to be utilized as "dirty" chips (with bark not removed before chipping) and have no merchantable value that would exceed their value as dirty chips; limbs are also utilized as chips when whole-tree harvest systems are used. Chip trees are the noncommercial trees and are accounted as a percentage of total volume for each size class. Note that average tree volumes provided as inputs to OpCost are total volumes, including tops and limbs.

Transformations

A comparison of the variables listed in table 3 (required input variables) and table 4 (OpCost inputs) shows that while most are aligned, there are some required variables not provided by

BioSum. As each stand is processed, OpCost effects transformations to ensure that the input requirements for all 124 equations can be met. For example, OpCost estimates average d.b.h., which is required by at least some production functions for most equipment types, by inverting formulas associated with common log scale rules such as the International ¼-inch rule (Grosenbaugh 1952) and Scribner's Decimal C (Bruce and Schumacher 1950), to predict d.b.h. from BioSum-supplied average volume per tree. In several cases, it is necessary to estimate average interterm distance (which is required by at least some of the sawyer, CTL harvester, and feller-buncher equations) from TPA supplied by BioSum. Mean inter-tree distance is estimated from TPA as follows: Intertree distance = $\sqrt{(43560\ /\ TPA)}$

Because some equations estimate time required per unit mass, OpCost calculates mass per acre, by tree size class and in total, by multiplying BioSum-supplied average wood density by average tree volume and TPA. Depending on the referenced equations used, some volumes are converted to cubic feet, board feet, or cords per acre. All volumes and masses are also converted to metric units (cubic meters per hectare or kilograms per hectare) to fulfill the requirements of equations defined in metric units.

Filtering

When processing each stand, OpCost applies the rejection criteria associated with each of the 124 equipment equations to eliminate equations deemed unsuitable for estimating costs for that stand. Typically, these rejection criteria are derived from the range of an attribute reflected in the empirical data on which an equation was fit. Any of the attributes may be the basis for rejection criteria. For CTL harvesters and feller-bunchers, D.B.H. is an important filter; for yarders, distance to landing and slope might be attributes with rejection criteria, but the criteria will differ among equipment types and among equations for a given equipment type, thus the sets of equations used for any two stands that are in some respects similar, may still differ.

Size Class Specific versus Total/Average

Equations differ as to whether or not they take stand-level- or size-class-specific inputs, even for a given equipment type. For those that operate with individual size classes (e.g., CT, SLT, and LLT), harvested tree descriptors such as average volume and TPA are processed for a specific size class to obtain equipment time associated with that size class. Ultimately, the equipment times for all size classes are summed. With mixed systems, for example when only large log trees are manually felled, sawyer equations would use only the LLT descriptors. Because the requirements differ among equations, OpCost calculates overall stand averages and totals for all harvested trees, as noted under "Transformations" above, so that these are available for the equations that rely on them.

OpCost Workflow

For a given equipment type, OpCost calls a machine-specific function. For a yarder time estimate, for example, it would call the yarder function, passing two arguments: the input variables generated by BioSum via the opcost_input table and the list of candidate production functions for that equipment. Parsing each opcost_input record, that function would reject inappropriate yarder equations, create the necessary transformed attributes, estimate yarder times per unit of material for all the appropriate equations, and adjust time per tree unit to time per acre for each tree size class separately, if necessary. It would then sum across size classes, compute the average over estimates from all yarder equations, multiply the estimated time per acre by yarder unit cost in dollars per hour and return that cost component to be used when adding up the cost of all machines used on that stand, at that time, with that harvest system.

When using OpCost SE, harvest year can be included as an input and optionally, if a discount (interest) rate is provided, harvest cost estimates can be expressed in present or future value terms. When using OpCost BE with BioSum, discounting and inflation considerations are handled within the BioSum modeling framework.

Putting It All together

Figure 1 summarizes the seven major processing steps that occur within OpCost to compute the multiple components of harvest cost and combine them into an estimate of complete harvest cost per acre. Model output is deterministic in that a given set of stand inputs will always produce the same results as long as the same FVS stand projection (output) data are included. Note that, apart from BioSum, users sometimes choose to run FVS in a stochastic mode. Thus, OpCost users that repeat growth and yield predictions for the same stand multiple times in FVS prior to post processing with OpCost should expect that projected stand conditions may differ owing to inclusion of random numbers in underlying FVS code. This, in turn, may result in variability among associated OpCost treatment cost estimates.

OpCost Stand-alone Edition (SE)

OpCost SE is designed to operate without BioSum, and relies on an installed version of R 3.0 or greater (R Development Core Team 2016), with the RODBC (Ripley and Lapsley 2016), Shiny (Chang et al. 2016), and ggplot2 (Wickham 2009) packages installed and loaded. There are three required script files that are available for download, and all three files should be saved to a single reference folder in the analyst's computer. The files are called ui.r, server.r, and OpCostShiny.r. These files are available at the following URL: http://www.uidahoforestoperations.com/forest-operations-modeling.html. Each R script needs to be stored in the same directory on the user's computer so the server code can locate the other files. After the files have been loaded, they are then available to open in the R environment using either the R console or a development environment such as RStudio. The user then runs the Shiny-based OpCost Graphical User Interface in R and the app will appear in the computer's default web browser (tested with Internet Explorer) allowing for a simple, interactive and intuitive user interface. The inputs are the same as for OpCost BE and can be stored in either comma or space delimited text files.

Once the application is open in the browser window, the user begins by navigating to and selecting the input file. A progress bar provides feedback as this data is loaded and processed, typically within seconds. When the progress bar achieves 100 percent, the estimated costs per acre using the harvest system chosen by the user will appear in a table, with one row per stand ID and prescription year. Each table generated by OpCost may be selected and copied or downloaded as a text file using the table buttons. After the table appears, the user also has the option of selecting the "ideal" table, present cost of future treatments, and ideal present costs of future treatments. The present cost and ideal present cost tables contain the discounted costs of harvest prescribed for a future year. The analyst also has the ability to select a different state, with different assumed machine rates, or can designate custom machine rates using the third tab of the interface by selecting the designated check box, which activates the custom machine rate table.

Each loaded table actively updates as an analyst adjusts prescription year or machine rates, streamlining the process for experimenting with different scenarios. After creating these tables, the analyst can proceed to the figures page where each of the tables previously created can be displayed graphically. The figures page also provides a graphical cost comparison of the analyst-defined harvest system and the system estimated by OpCost as the lowest cost alternative. Note that figures will only be viewable after tables have been created. Figures can be copied and pasted to a separate document, or saved to disk, using the menu options that appear when right-clicking on the image.

To run another set of stand operations without starting a new session, save the output data, if desired, before loading a new dataset. OpCost SE does not automatically save outputs to files or maintain previous estimates in memory so any information from the previous analysis will be overwritten when new data are loaded. All output tables and figures will also be lost if exiting the program without first saving these to disk.

Future Directions

OpCost’s adaptable design enables it to handle a wide variety of systems and to accommodate new systems yet to be developed. Development is underway to enable production rates for new kinds of equipment to be implemented by entering the parameter and predictor variables associated with production and machine rates for new equipment and systems into a preformatted Excel table. The production function supplied should include output in total treatment time (delay-free Productive Machine Hours), expressed on a per-acre basis. Users should also supply the key components of equipment machine rates: purchase price, utilization rate, etc. See, e.g., Brinker et al. 2002 for a description of machine rate calculations. The user-supplied production function parameters and machine rates will be incorporated into system-level logging cost predictions as described in, e.g., Keefe et al. (2014). A sample Excel table and details on how this table will be accessed by OpCost will be documented in the release notes accompanying a future OpCost version.

One of the great benefits of providing OpCost in the open-source R framework is that it facilitates coordinated growth, development, and testing by a more expansive set of users than did earlier Excel and VBA-based versions of FRCS and related models. We anticipate making OpCost available as part of a package of R functions in the future in order to foster widespread distribution and use, especially for automated landscape-scale analyses. In its current incarnation, OpCost relies on stand-level FVS summaries of harvested trees. We envision refinements to the model that would base cost estimates on the full FVS tree list data, instead of summary metrics, potentially leading to greater accuracy and higher resolution simulation of operational logistics.

English Equivalents

When you know:	**Multiply by:**	**To find:**
Acres	0.4046	Hectares
Cubic feet	.0283	Cubic meters

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Table 2.1—Utilization of wood in tops and limbs varies by harvest system category and slope

Harvest system category	Slope	Outcome for tops and limbs
1	Low	Left in the woods
2	Low	Forwarded to landing for chipping
3	High	Left in the woods
4	Any	Except for large log trees, forwarded to landing for chipping
5	Any	Forwarded to landing for chipping only when size is submerchantable or species is noncommercial

Table 2.2—Harvest systems options available in the OpCost model and the equipment types used in each system

Harvest system name	**Equipment types used**	**Harvest system category**
Ground-based manual whole tree	Sawyer, skidder, processor, loader, chipper	2
Ground-based Mechanical whole tree	Feller-buncher, skidder, processor, loader, chipper	2
Ground-based cut-to-length (CTL)	CTL harvester, forwarder, loader, chipper	1
Ground-based manual log	Sawyer, forwarder, loader, chipper	1
Cable manual whole tree	Sawyer, yarder, processor, loader, chipper	4
Cable manual whole Tree/log	Sawyer, feller-buncher, processor, loader, chipper Note: all large trees are assumed to be manually bucked into logs prior to yarding	5
Cable manual Log	Sawyer, yarder, loader, chipper	3
Cable CTL	CTL harvester, yarder, loader, chipper	1
Helicopter manual whole Tree	Helicopter, sawyer, processor, loader, chipper	3
Helicopter CTL	Helicopter, CTL harvester, loader, chipper	1
Shovel manual whole tree	Shovel, sawyer, processor, loader, chipper	4

Table 2.3—Sources of equations relied on by OpCost to estimate machine time requirements for forest harvest operations, by machine type, and the set of input variables that these equations draw from as independent variables for use in predicting machine time per unit tree volume or mass

References for production equations, by machine type	Required independent variables
Sawyer:	
Behjou and Majnounian 2009	Diameter at breast height (DBH)
Ghaffariyan et al. 2012	Total volume
Hartsough et al. 2001	Piece volume
Klepac et al. 2011	Distance between trees
Kluender and Stokes 1996	
Lortz et al. 1997	Slope
Visser and Spinelli 2012	
Wang et al. 2004	
Cut-to-length (CTL) harvester:	
Acuna and Kellogg 2013	DBH
Adebayo et al. 2007	Slope
Berhongaray et al. 2013	Trees/acre
Bolding et al. 2002	Total volume
Bolding and Lanford 2001	Piece volume
Drews et al. 2001	
Eliasson 1999	Species group
Hiesl 2013	
Hiesl and Benjamin 2012	Distance between trees
Jiroušek et al. 2007	
Kärhäet et al. 2004	
Jiroušek et al. 2007	
Keegan et al. 2002	
Klepac et al. 2006	
Klepac et al. 2011	

Numinen et al. 2006	
Visser and Spinelli 2012	
Skidder:	
Adebayoet al. 2007	
Bolding et al. 2002	DBH
Boswell 1998	Piece volume
Ghaffariyan et al. 2012	Species group
Hiesl and Benjamin 2012	One-way yarding distance
Keegan et al. 2002	Total volume
Kluender and Stokes 1996	Trees/acre
Wang et al. 2004	Slope
Feller-buncher:	
Adebayo et al. 2007	
Berhongaray et al. 2013	DBH
Bolding and Lanford 2001	
Boswell 2001	Distance between trees
Dykstra 1976	
Hartsough et al. 1997	Piece volume
Hartsough et al. 1997	Trees/acre
Hartsough et al. 2001	Species group
Hiesl 2013	
Hiesl and Benjamin 2012	
Kärhä et al. 2004	
Kluender and Stokes 1996	Trees/acre
Spinelli et al. 2007	Slope
Wang et al. 2004	
Helicopter:	
Christian and Brackley 2007	Piece weight
Dykstra 1976	One-way yarding distance
Flatten 1991	Elevation
Flatten 1991	Piece volume
	Trees/acre

Forwarder:	
Acuna and Kellogg 2013	One-way yarding distance
Bolding et al. 2002	Piece volume
Bolding and Lanford 2001	Slope
Drews et al. 2001	
Dykstra 1976	
Hiesl 2013	
Jiroušek et al. 2007	Trees/acre
Jiroušek et al. 2007	Total volume
Kluender and Stokes 1996	DBH
Numinen et al. 2006	Weight
Sirén and Aaltio 2003	
Cable:	
Drews et al. 2001	Trees/acre
Aubuchon 1982	Slope
Dykstra 1976	Piece volume
Boswell 2001	Piece weight
LeDoux 1987	
Hartsough et al. 2001	
Huyler and LeDoux 1997	
	One-way yarding distance
Chipper:	
Bolding et al. 2002	Piece volume
Bolding and Lanford 2001	Species group
Cuchet 2004	
Spinelli and Magagnotti 2014	DBH
Shovel:	
Fisher 1986	One-way yarding distance
Sessions and Boston 2013	Elevation
Wang and Haarlaa 2002	Piece volume
	Trees/acre
	Weight
Stroke-boom delimber:	

Ghaffariyan et al. 2012	Piece volume
Hartsough et al. 2006	DBH
Hiesl 2013	
Spinelli and Magagnotti 2010	Species group

Table 2.4—OpCost inputs and what they mean

Column	Input Item	Description
1	Stand	Stand identifier (condition id + rxPackage + rx + rxCycle)
2	Percent slope	Slope
3	One-way yarding distance	Distance in feet between volume centroid of the stand and nearest road
4	YearCostCalc	Year of harvest (used only in OpCost stand-alone edition)
5	Project elevation	Stand elevation in feet above mean sea level
6	Harvesting system	Name of harvest system
7	Chip trees per acre	Trees per acre (TPA) of chip trees
8	Chip trees Merch As Pct Of Total	Percentage of chip tree volume in merchantable-size wood (used for harvest systems that do not utilize tops and limbs)
9	Chip trees average volume(ft^3)	TPA weighted average of total volume
10	Chip trees average density (lb/ft^3)	TPA and volume weighted average wood density of all chip trees

11	Chip tree hardwood percent	TPA and volume weighted percentage of chip tree volume that is in hardwoods
12	Small log trees per acre	TPA of small log trees
13	Small log trees Merch As Pct Of Total	Percentage of small log volume in merchantable sized wood
14	Small log trees ChipPct_Cat1_3	Percentage of harvested small log volume that will be chipped under harvest systems in category 1 or 3
15	Small log trees ChipPct_Cat2_4	Percentage of harvested small log volume that will be chipped under harvest systems in category 2 or 4
16	Small log trees ChipPct_Cat5	Percentage of harvested small log volume that will be chipped under harvest systems in category 5
17	Small log trees total average volume(ft^3)	TPA weighted average total volume per small log tree
18	Small log trees average density(lb/ft^3)	TPA and volume weighted average wood density of small log tree volume

19	Small log trees hardwood percent	TPA and volume weighted percentage of small log tree volume that is in hardwoods
20	Large log trees per acre	TPA of large log trees
21	Large log trees Merch As Pct Of Total	Percentage of large log tree volume in merchantable sized wood
23	Large log trees ChipPct_Cat1_3_4	Percentage of harvested large log tree volume that will be chipped under harvest systems in category 1 or 3 or 4
24	Large log trees ChipPct_Cat2	Percentage of harvested large log tree volume that will be chipped under harvest systems in category 2
25	Large log trees ChipPct_Cat5	Percentage of harvested large log tree volume that will be chipped under harvest systems in category 5
26	Large log trees total average vol(ft^3)	TPA weighted average total volume per large log tree
27	Large log trees average density(lb/ft^3)	TPA and volume weighted average wood density of all the large log tree volume

28	Large log trees hardwood percent	TPA and volume weighted percentage of large log tree volume that is in hardwoods
29	BrushCutTPA	TPA of brush cut trees
30	BrushCutAvgVol	TPA weighted average bole+branch volume of brush cut trees
31	RxPackage_Rx_RxCycle	Code indicating silvicultural sequence, prescription and Forest Vegetation Simuator cycle under which trees were harvested
32	BioSum_cond_id	Needed for table joins
33	Rxpackage	Needed for table joins
34	Rx	Needed for table joins
35	Rxcycle	Needed for table joins
36	Move-in hours	Time required to move-in and setup logging equipment
37	Harvest area assumed acres	Area assumed for the size of the harvest operation

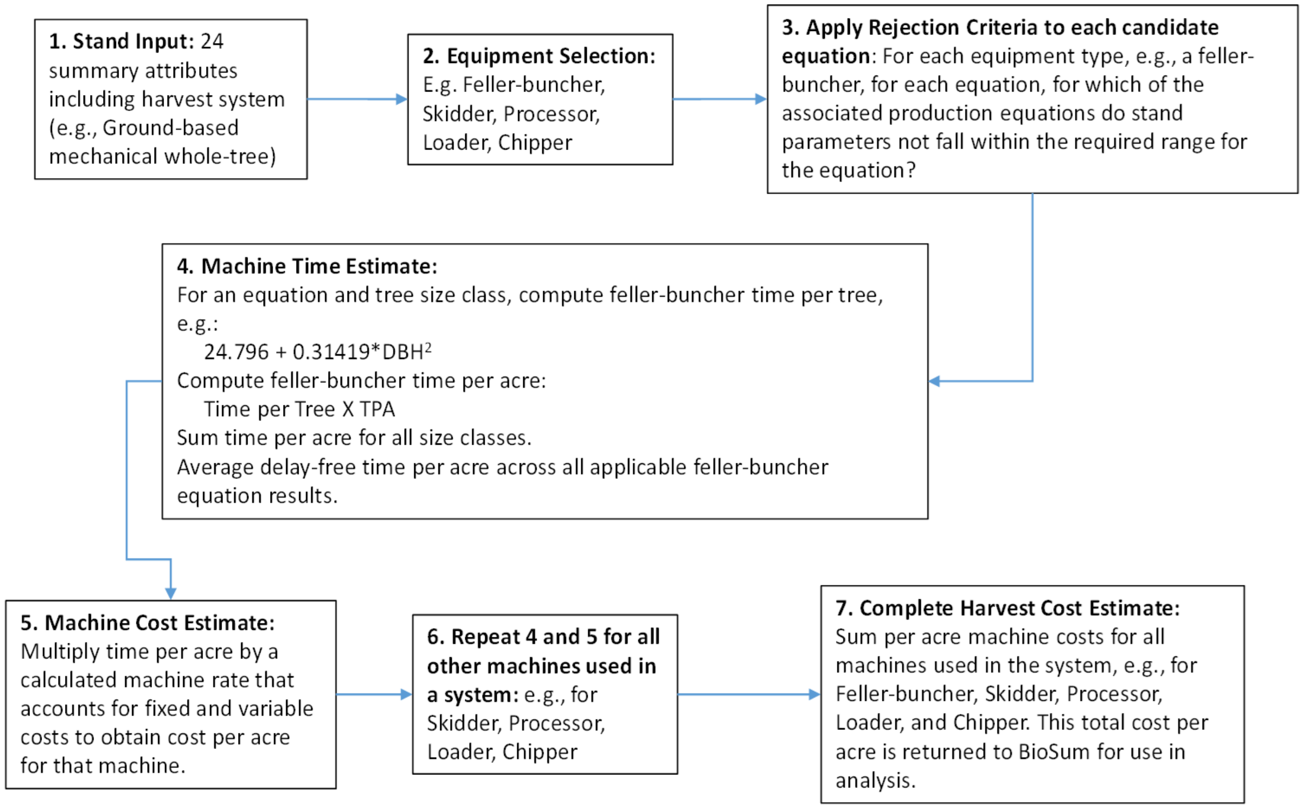

Figure 2.1—Example of work flow within OpCost to estimate complete harvest cost for a stand harvested via ground-based mechanical whole-tree harvest system.

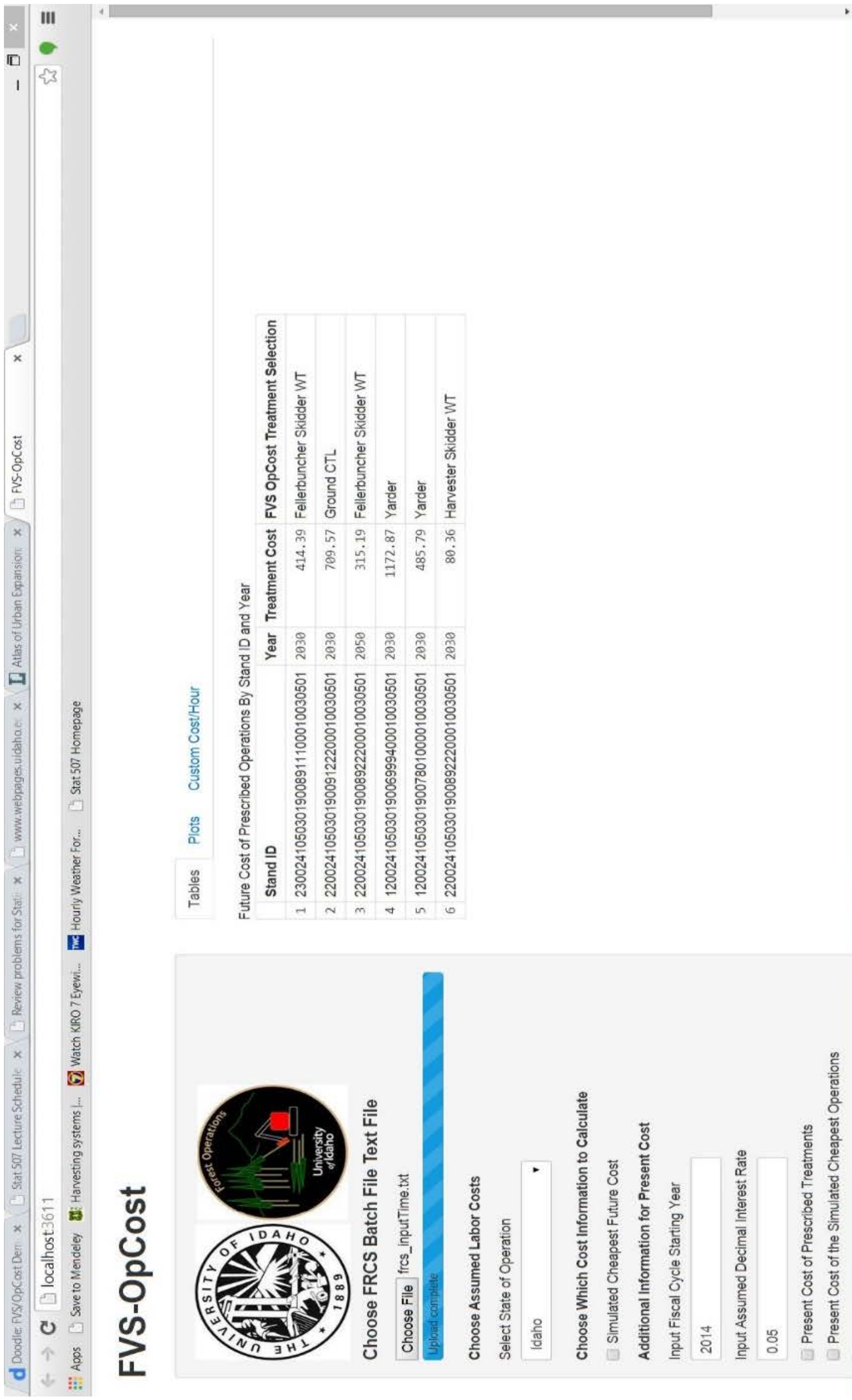

Figure 2.2—Initial "Tables" page in OpCost stand-alone.

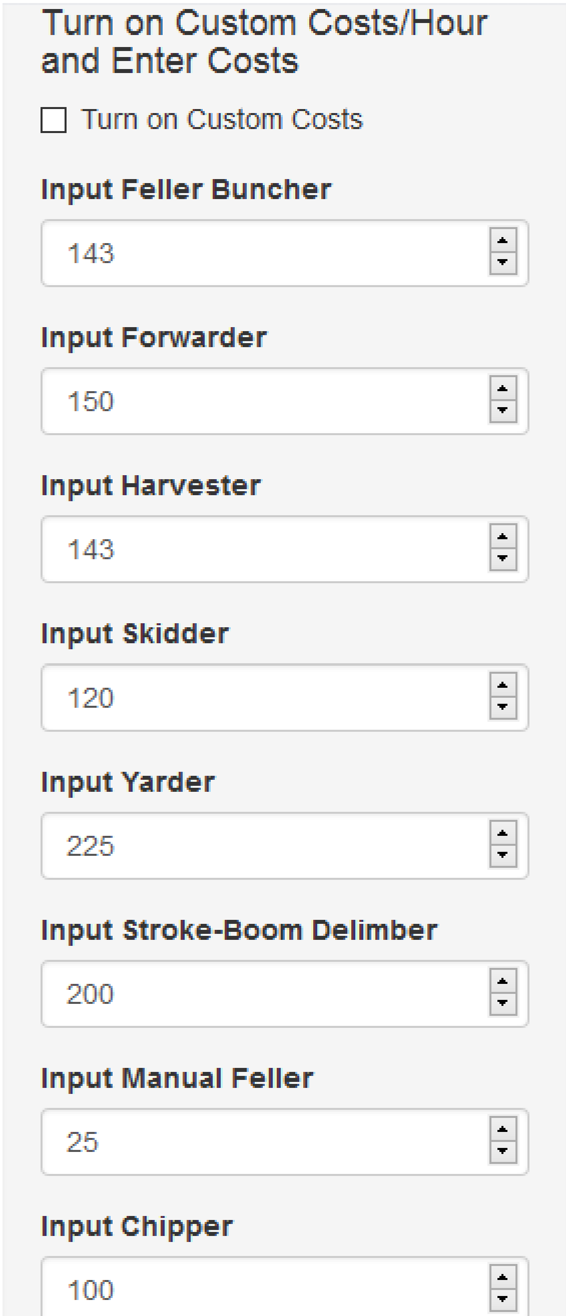

Figure 2.3—“Custom Cost” page in OpCost stand-alone edition.

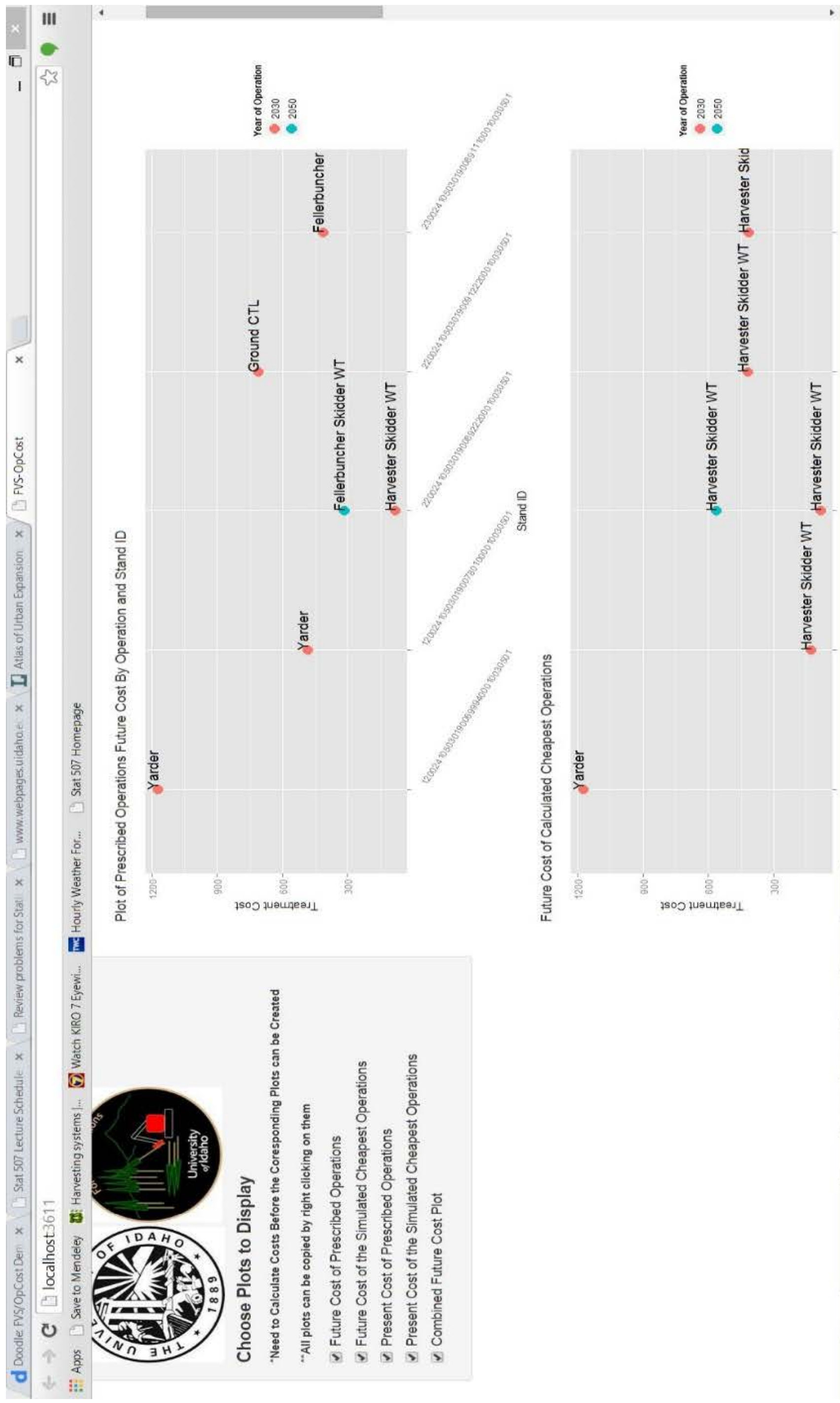

Figure 2.4—"Plots" page of OpCost stand-alone edition.

[1]The use of trade or firm names in this publication are for reader information and do not imply endorsement of the U.S. Department of Agriculture of any product or service.

Chapter 3:

Validation of the OpCost logging cost model using contractor surveys

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 impor-tant 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 wide-spread 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 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 out-put 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 thou-sand 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 eco-logical and economic outcomes in both time and space. At various stages, OpCost transforms stand prescription

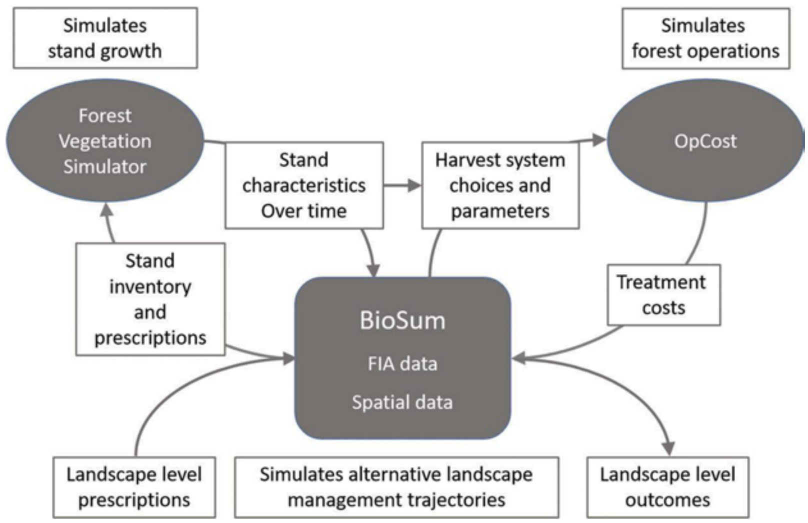

Figure 3.1. Relationship between OpCost and the Forest Vegetation Simulator (FVS) within the Bioregional Inventory Originated Simulation Under Management (BioSum) framework when conducting analysis of forest management scenarios over large, regional spatial extents (>1 million ac, or 404,685 ha) using 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.

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 across 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.

Table 3.1. 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)
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 (thou-sand 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 pro-vided 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 pre-dictions 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 and 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 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.

Table 3.2. 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

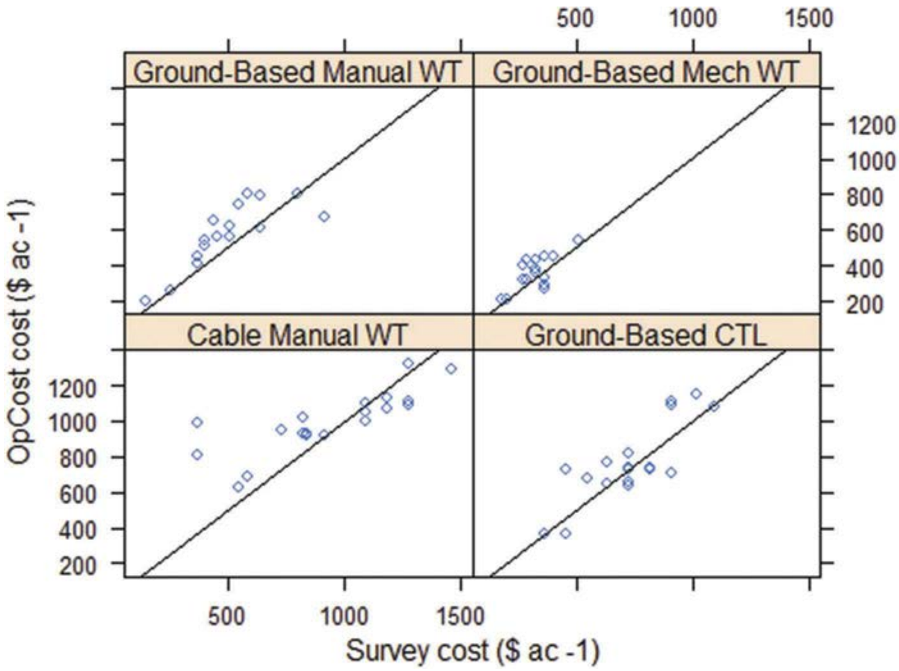

Figure 3.2. Scatterplot of OpCost estimated harvest cost vs. logger estimated harvest costs for all timber sale prospectus vignettes

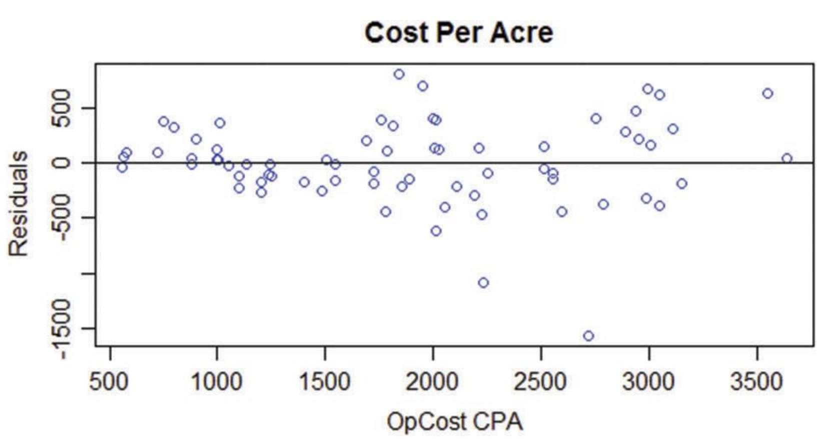

Figure 3.3. Model residuals vs fitted values for all predicted costs per unit area, including all harvest systems evaluated in this study. Fitted values on the X-axis are the OpCost-simulated costs per unit area for each timber sale prospectus vignette; residuals are the difference between costs per unit area (ac) estimated by contractors and the corresponding treatment cost predicted using OpCost.

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 cap-able 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 those.

Table 3.3. 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	

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.

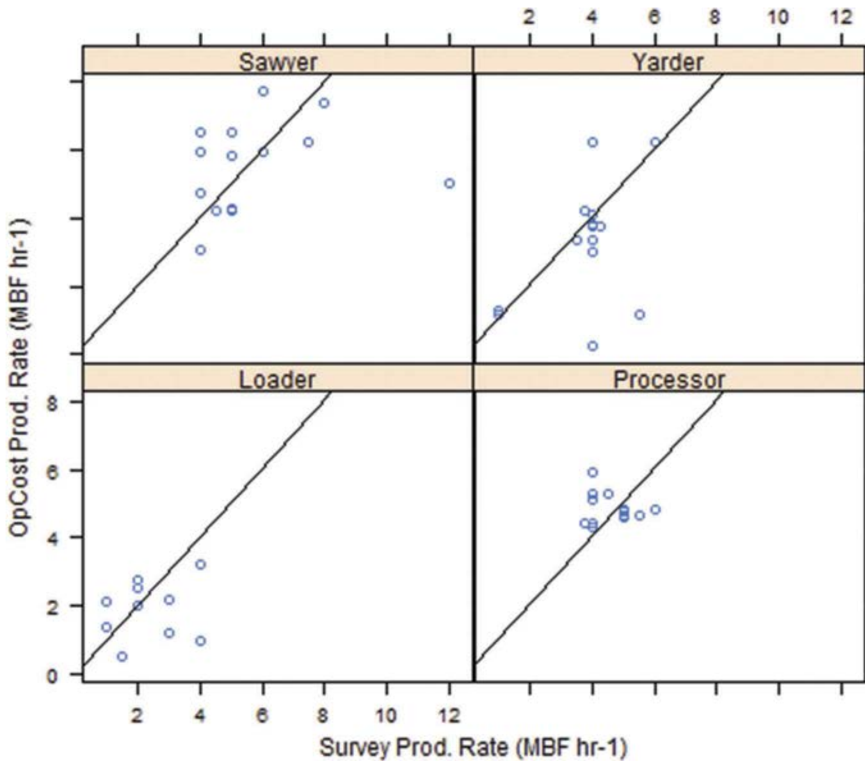

Figure 3.4. Scatterplot of OpCost estimated production rates vs. logger estimated production rates for all timber sale prospectus vignettes by equipment type within the cable-based manual whole tree system.

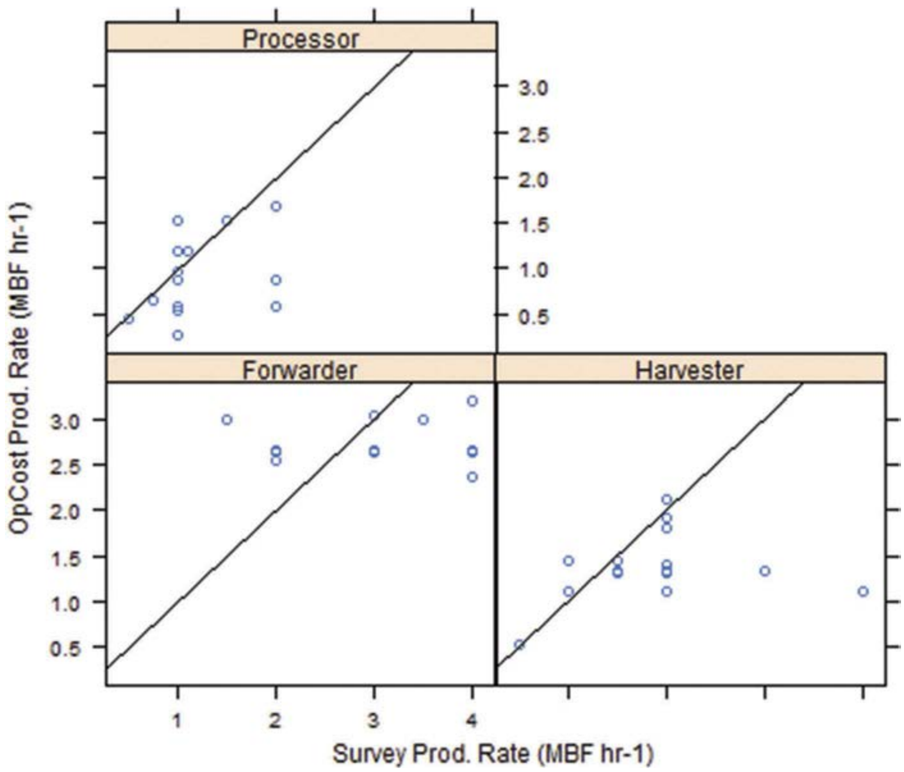

Figure 3.5. Scatterplot of OpCost estimated production rates vs. logger estimated production rates for timber sale prospectus vignettes by equipment type within the ground-based mechanical cut-to-length system.

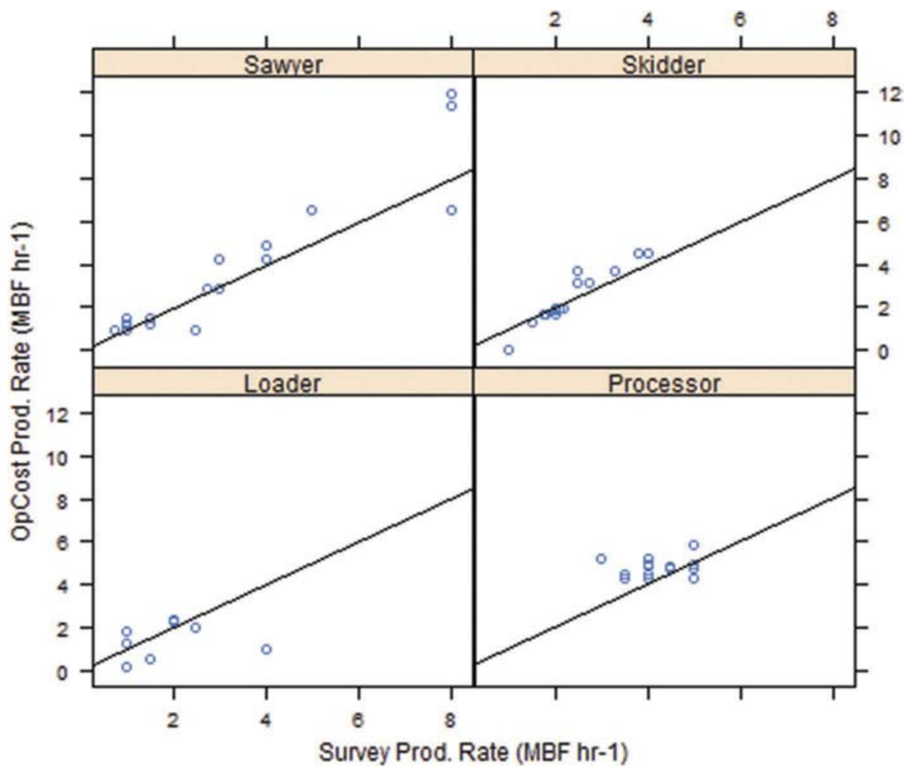

Figure 3.6. Scatterplot of OpCost estimated production rates vs. logger estimated production rates for timber sale prospectus vignettes by equipment type within the ground-based manual whole tree system.

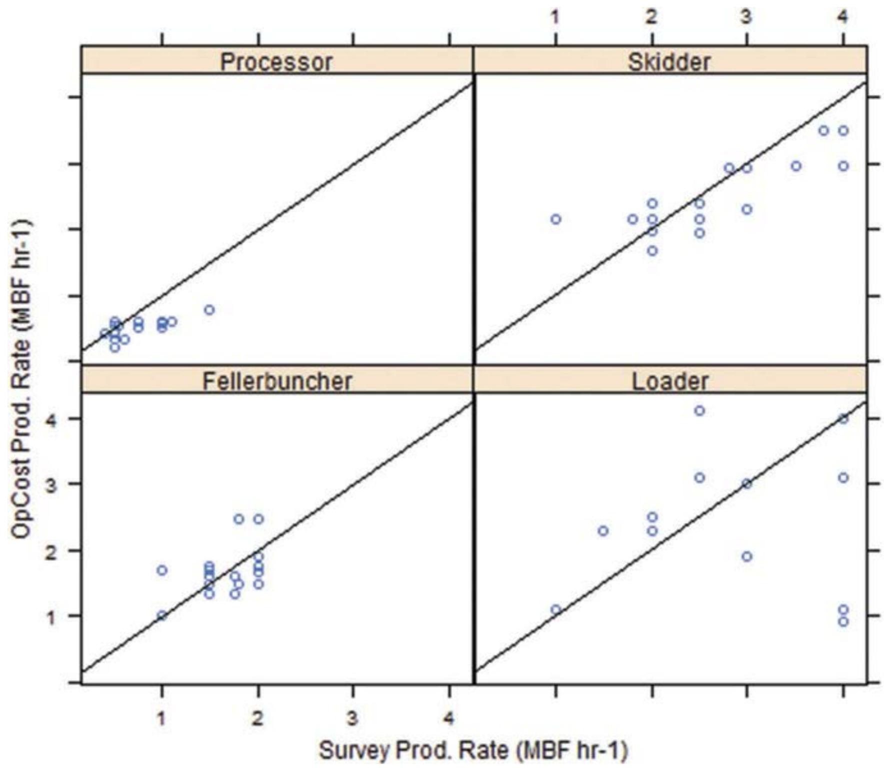

Figure 3.7. Scatterplot of OpCost estimated production rates vs. logger estimated production rates for all timber sale prospectus vignettes by equipment type within the ground-based mechanical whole tree system.

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 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, land-owners, 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. 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 to make 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.

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 sub-models 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 to make 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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Chapter 4:

Conclusions

Two of the most effective methods of reducing the density and the risk of catastrophic fire in western forests in the United States is by various physical active management. While many management activities have economic gain from the sale of harvested materials, all of them will have costs associated with the activities. To fully understand the economic impact of forestry activities managers, researchers, and the public need to have an estimate of what the operations will cost on the landscape. Previous designs at understanding the harvest costs associated with forestry activities (FRCS, Hartsough, Fight, & Noordijk, 2006) have provided vital economic information, but have lacked comparative testing and features required for comparative testing for the BioSum project. The Forest Operations Lab at the University of Idaho has addressed these needs with OpCost developed in the R statistical environment.

Developing the OpCost environment required identifying production equations related to the harvesting systems most commonly used in modern day forestry. OpCost does include 11 different harvesting systems, but the system is easily updatable to include novel system currently such as tethered harvesting, and remotely operated systems. This inherent flexibility is an advantage because as logging operations develop more streamlined systems, OpCost will be able to include these operations in a preconditioned analytical environment capable of producing comparative numbers and graphics. One of the most important developments in OpCost related to research and comparative analysis is its ability to simultaneously estimate each potential operation given the stand conditions and provide the cheapest estimation in an output table. By having the option to quickly compare different harvesting options appropriate for the stand conditions allows the analyst to potentially pick a cheaper option to study further.

To increase the faith in the numbers generated by the model, a sample dataset was needed to compare the estimates that were generated. By using a mixed method surveying technique involving mailed and face-to-face questionnaires representing simulated forest harvests with a fuels reduction component. Each of the different adaptions of the forest operations were run through OpCost and the generated estimates were compared to the cost estimates from surveyed professional loggers. This analysis provided observations of occurring trends within the model as well as the accuracy of the generated costs.

Appendix 1: Logging Cost Survey

Oregon Survey

Ground-Based Mechanical Cut-to-Length

Contractor Costing Sheet

General Instructions:

For this questionnaire we ask that you bid on a forest harvesting operation that involves cut-to-length tree harvesting using a ground-based system with a **cut-to-length processor, forwarder, and a loader** at the landing. We want to know what you think the production rate would be for each part of the harvesting system, as well as the cost per MBF for the different components (e.g. sawing, yarding, processing, and loading). The stand information we provide below includes a stand characteristics table with additional details such as slope, topography, and yarding distances. After the map and harvest description you will find an area to write your estimates, as well as a place to provide any additional details you were thinking of while developing your estimate. For simplicity, assume that all the ground illustrated is ground-based terrain only. Please do your best to estimate what it would cost your crew to remove the material from the stand based on the information given. Also, please do not include any move-in costs in your estimate.

Road Construction: We are assuming that all road construction is already complete with no other road developments required. However, after looking at the map do you feel that more road construction is required?

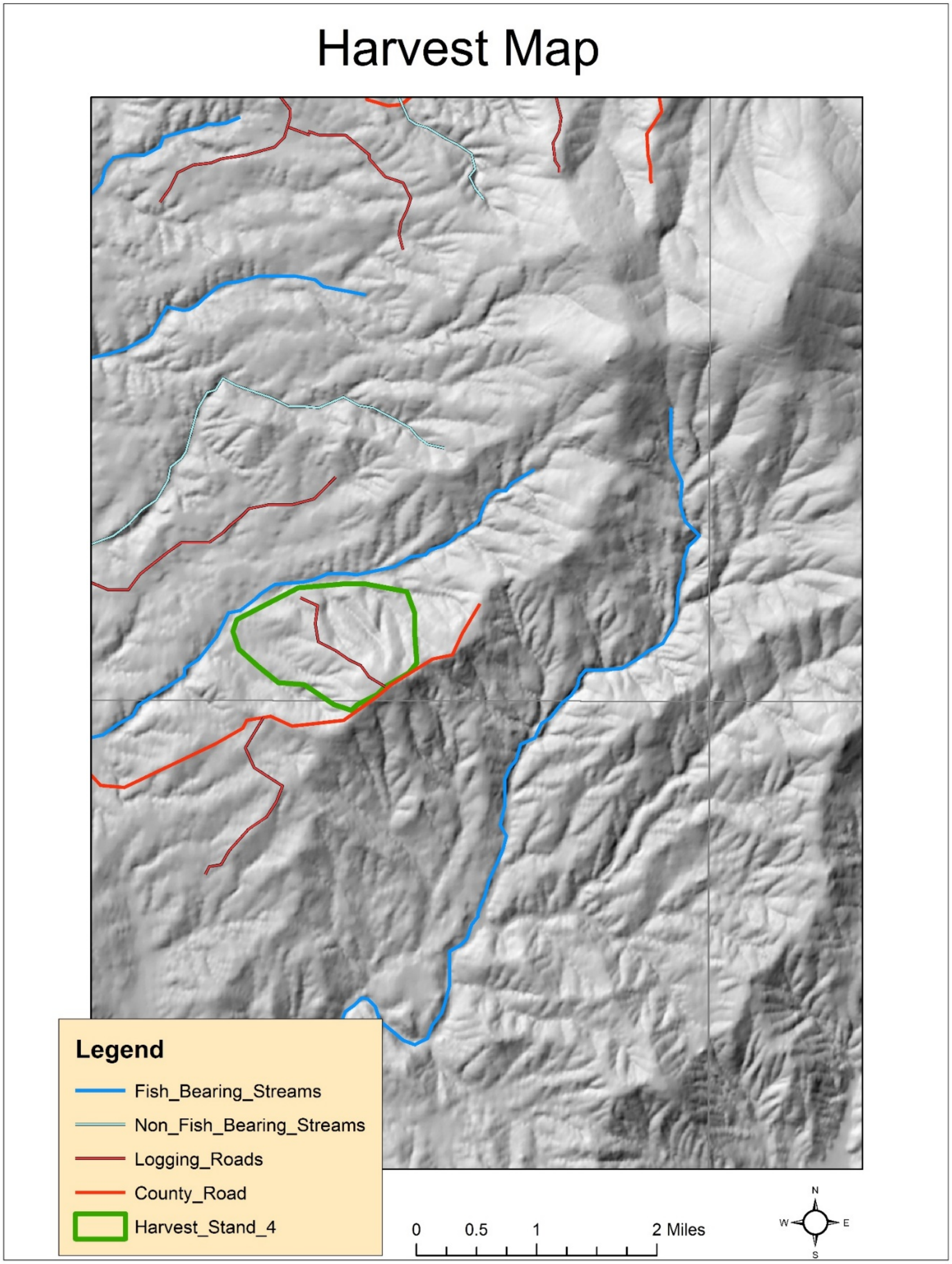
Yes: Please provide the amount and possible cost.______________________________

No: Please check:__________

Stand and Harvest Description:

Stand Infromation	
Acres	89
Avg Slope	14%
Road Construction	0 Miles
One-way Yarding Distance	0.3 Miles

Harvest Summary					
Spp	Trees/Ac.	Avg. DBH	Net MBF/Ac.	Logs/Ac.	Basal Area
Doug Fir	72.1	19.1	22	148	143.8
Hemlock	38.9	17	8.9	85.8	61.3
Totals:	111	18.05	30.9	233.8	205.1


Harvest Map
Legend
Fish_Bearing_Streams
Non_Fish_Bearing_Streams
Logging_Roads
County_Road
Harvest_Stand_4
0 0.5 1 2 Miles
N
W
E
S

Harvesting Operation Survey:

Cut-to-Length Processer

What is the make and model of the cut-to-length processor? ______________________________

What is the expected production rate for the cut-to-length processor (MBF/Hour)___________

What is the estimated total cost per MBF for the cut-to-length processor (excluding delay time)?____

What is the total number of expected productive hours per 8 hour working day?_____________

What is the total number of hours of expected delay time (operational, mechanical, etc.) per 8 hour work day?____

Forwarder

What is the make and model of the forwarder? ____

What is the expected production rate for the forwarder (MBF/Hour) ________________________

What is the estimated total cost per MBF for the forwarder (excluding delay time)? ___________

What is the total number of expected productive hours per 8 hour working day? _____________

What is the total number of hours of expected delay time (operational, mechanical, etc.) per 8 hour work day?____

Loader

What is the make and model of the loader? ____

What is the expected production rate for this loader given these conditions?_________________

What is the estimated total cost per MBF for the loader (excluding delay time)?______________

What is the total number of expected productive hours per 8 hour working day?_____________

What is the total number of hours of expected delay time (operational, mechanical, etc.) per 8 hour work day?____

Are there any additional details you would like to add?

Approximately how many hours would it would take your operation to complete an acre of this operation?

Optimum Harvesting Equipment:

After the initial survey, we also want to understand what the ideal machinery loggers would use given these conditions. Please take a moment and describe what kind of system and equipment you believe would result in the highest efficiency and lowest cost to complete the operation. Please be as detailed as possible, e.g. all the components (harvesting, transporting, processing) and make and models of machinery if possible.

Ideal Harvesting System:

Are there any additional details you would like to add?

Please return the survey.

We Thank You for Your Time and Effort!