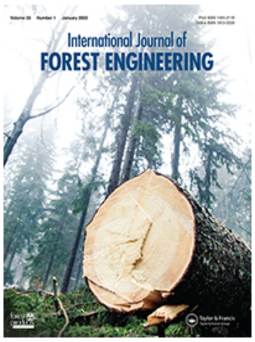

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The effect of tree and harvester size on productivity and harvester investment decisions

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ABSTRACT
Long-term machine-derived data sets comprising 140,000 trees were collected from four harvesters of equal age and similar working conditions, into two machine size classes, viz. two Ponsse Bears and two smaller Ponsse Beavers. Productivity functions for each size class were modelled using a nonlinear mixed effects approach. Based on these functions, unit costs and their sensitivity to utilization rates and cost of capital were assessed.

Results showed that despite considerably higher capital costs (32%) on the Bear, a 50% higher mean productivity resulted in a unit cost only 17% higher than the Beaver in a disadvantageous scenario (high interest rates and low utilisation), and a 6% lower unit cost than the Beaver in an advantageous scenario (low interest and high utilisation), within the range of tree sizes observed. Between these extremes, only marginal differences in unit costs were observed. This demonstrates that the difference in ownership and operating costs between larger and smaller harvesters is largely negated by the difference in productivity rates.

These results can provide useful insight into timber harvester investment decisions. Harvesters from two adjacent size classes can be used interchangeably at the same unit cost within a wide range of tree sizes despite productivity differences. It should be noted that increased repair costs and an eventual reduction in expected economic lifetime on a smaller harvester, or the negative effects of using a larger harvester in smaller trees, e.g. thinning operations, were not taken into account in this work.

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StanForD; nonlinear mixed effect models; CTL; harvesting; saw timber; machine costing; sensitivity analysis

Introduction

Purpose-built timber harvesters are designed to achieve the high rates of productivity necessary in offsetting the high cost of the technologies incorporated into their build. When these rates are not consistently achieved for reasons like poor operator performance or extrinsic factors such as unanticipated tree sizes, tree size distributions, or terrain conditions, the arguments supporting the investment or replacement decision are often invalidated (Melander and Ritala 2020). The most opportune time for ensuring a good match between technical machine specifications and the attributes of the forest is at the time of investment or replacement (Cantú et al. 2017). However, even if this opportunity is used well, meeting varying delivery contracts often requires harvesters to be deployed in a wider range of forest conditions than originally anticipated. This is exemplified by Diniz et al. (2020), who consider a replacement policy for harvesters working with a “central range” of 0.26–0.66 m^3 tree sizes. Variability in tree size is especially accentuated in seminatural managed forests where regeneration and ingrowth of other species commonly occurs, such as the boreal forests of Fennoscandia (Eriksson and Lindroos 2014). Planted forests in contrast, offer opportunities for rationalization and uniformity that are not available to more natural forest management regimes, and these make up a significant and increasing share of the market for CTL technology. The extent of planted forests expanded from 168 M ha to 278 M ha between 1990 and 2015 and they now constitute a significant proportion of global wood supply, this implies a similarly high and anticipated increase in the degree of mechanization (Keenan et al. 2015). Plantation stands or compartments are delineated according to common soil, topographic, and microclimatic conditions, with the express purpose of making them as homogeneous as possible. Tree uniformity can be further manipulated through forest management interventions such as the use of improved genetic material, minimizing planting stock mortality (Rolando et al. 2003), ensuring effective and timely tending (Little and Rolando 2001) and multiple and directed thinning operations (Donald 1977). The aim of these intensive management interventions is to increase overall volume yield (De Moraes Gonçalves et al. 2004), improve uniformity and maximize allocation to specific trees and log classes.

This uniformity of stands and operations in plantation forests, and the more precise information available on forthcoming volumes and tree sizes, provides a reliable basis for determining the size of the harvester to be purchased (Ledoux and Huyler 2001). However, considerable within-site variation in stand and tree attributes is still observed within intensively managed planted forests (Saremi et al. 2014). This, together

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with the challenges that operations managers face in finding the right stands to meet production targets, adds uncertainty to the machine investment decision. In compensating for this uncertainty, a prospective machine buyer might prefer to overcapitalize on the machine rather than risk not having the technical capacity to carry out certain jobs (Diniz and Sessions 2020). It is also likely that this tendency to overcapitalize would be stronger for a private machine buyer with limited insight into the yield forecasting pipeline than for a forest-company based purchaser who has full access to such predictions.

It is well known that tree volume-dependent productivity curves for different machine sizes level out with increasing tree size, albeit at differing thresholds. At the same time, differences in productivity between machines of different sizes in smaller dimensioned timber are more marginal than they are in larger dimensions (Eriksson and Lindroos 2014). Further, in countries applying CTL technology in larger plantation forest industries, the operator wage typically constitutes a smaller proportion, and depreciation a larger proportion, of the overall machine cost than it would in developed economies (Dembure et al. 2019; McEwan et al. 2020). This implies that the investment decision would be more sensitive to the purchase price of the harvester in transitional economies than in developed economies.

Harvester purchase price and depreciation is closely correlated with harvester size (Spinelli et al. 2011). Eriksson and Lindroos (2014) categorized the harvesters in their study into six size classes (S, M, L, XL, XXL, XXXL). They developed a set of productivity functions for each harvester size class and show how these machines are generally deployed in trees of differing mean size but that their productivity rates include a considerable overlap. The relationship between harvester productivity and tree size tapers off and even declines when tree size becomes too large for the machine to handle (Visser et al. 2009; Alam et al. 2014). However, this transition is variable, not always directly recognizable, and only seldom quantified, e.g. by Visser and Spinelli (2012).

Machine capability affects machine productivity, especially when moving, lifting and processing trees (Alam et al. 2014). In addition to tree size, tree form, in terms of shape, sweep, heavy branches, and forks have been found to reduce machine productivity; forks and branches being the most influential (Labelle et al. 2016). It is anticipated that larger machines are able to handle such defects with fewer problems than smaller machines.

All larger productivity studies are developed on the basis of StanForD data (Arlinger et al. 2012). A real issue for consideration when using follow-up data is the size of the measurement error component. When calibrated effectively, machine measurements are generally accurate and produce a high level of individual tree characteristic data (Alam et al. 2014; Brewer et al. 2018; Kemmerer and Labelle 2020; Strandgard and Walsh 2011; Strandgard et al. 2013). Under such conditions, the harvester head has been shown to measure log volume more accurately than established manual methods (Hohmann et al. 2017). However, it is also recognized that such follow-up studies reflect varying error terms.

The first objective of the presented study is to investigate how well one can distinguish between the optimal tree-size ranges for two different harvester size classes. The second objective is to use the obtained information on the optimal tree-size ranges to evaluate harvester investment decisions. The study is carried out in a plantation forestry setting where site factors other than tree size are kept as uniform as possible, making it possible to isolate the effect of harvester size on optimal tree-size range.

Materials and methods

Study area

The study area is situated on the eastern highveld of South Africa, centered at roughly 26.24° S and 30.48° E, at an altitude of 1750 m asl. Multiple fully mechanized cut-to-length harvesting machines were studied, namely Ponsse Bear and Ponsse Beaver machine models. These systems were deployed to harvest *Pinus* spp. (Slash pine, *Pinus elliotti*); patula pine, *P. patula*; and loblolly pine *P. taeda*) trees into various plywood veneer, saw timber and pulpwood assortments. The area was well suited to CTL mechanized operations as the trees were evenly spaced in rows, pruned to 5–7 m, and the terrain was predominately flat and with good ground conditions according to the terrain classification by Erasmus (1994).

Data acquisition

A data set comprising of roughly 12 months of harvester data from each of four different CTL harvesters working in pine clear-felling operations was acquired. These machines comprised two large capacity eight-wheeled Ponsse Bear (24.5 t, ~260 kW), and two smaller capacity six-wheeled Ponsse Beaver (17.5 t, ~150 kW) harvesters. The Bears were fitted with Ponsse H8 harvesting heads and the Beavers with the Ponsse H6 harvesting heads. These heads have a maximum opening of 74 cm and 60 cm respectively. The onboard computer (OBC) captured and stored data in the StanForD Classic formatted stem files (*.stm) (Arlinger et al. 2012). For this study only *P. patula* data were used, these tree records comprised the bulk of the tree data in the *.stm files from the machines (> 80% by volume). Each machine was calibrated before commencing operation at new compartments and these calibrations were checked and adjusted intermittently throughout the workday.

For the study, individual tree data were extracted from the data set, these data consisted of the following information: stem length, DBH, stem volume and felling and processing timestamp at single tree level. Time to harvest a target tree was derived from the timestamp difference between the felling cuts of two consecutive trees. This time was presented in seconds. Harvesting time for the tree includes all the time components that would be measured in a typical time study; travel/move, boom-out, fell, boom-in, processing, and clearing or placing harvesting slash and other delays as detailed in Ackerman et al. (2014a). Due to the nature of these data being collected automatically, it was not possible to distinguish between different work elements in the data set.

StandForD data processing

The obtained stem files contained a significant amount of data that was not suitable for the intended analysis, due to anomalies caused by dead and dying trees, issues with how the harvester measured the tree being felled and in some cases harvester operator judgment on log length optimizations. For this reason, the data were cleaned to remove any unsuitable or mismatched data points. The first step in cleaning the data was done by hybridizing the data cleaning methods used by Strandgard et al. (2013) for *P. radiata* and Olivera et al. (2016) for *Eucalyptus* spp. grown in Uruguay.

This included removing trees where:

- They were harvested at a point of delay (time to harvest a tree was greater than 300 seconds),
- Only one log was produced per tree,
- The stem length was less than 250 cm (the minimum log length produced).

The first step of data cleaning removed approximately 28% (~196,000 to ~140,000) of the observations. The initial cleaning observation reductions for the data are in range to those presented by Strandgard et al. (2013) of between 26 and 40%. This too was in a similar *Pinus* spp. It must also be noted that the 300 second tree harvesting time does include some shorter delays that are difficult to differentiate on long-term data sets. These can include; phone calls, smaller mechanical issues (i.e. saw-chain changes) and personal breaks.

These data were plotted and the range of the DBHs set. This working range encompasses the bulk of these tree data and is characteristic of mature patula pine (*P. patula*).

The tree sizes were spread across the DBH classes and the extreme observations (at the low and high DBHs) were clearly only made up of a few observations (Figure 1). For this reason, these data were then bounded between trees of a minimum 12.6 cm and maximum 52.5 cm. Details of the machine dataset are presented in Table 1. The total number of observations for each machine class differed as only the comparable clear-felling and not the thinning data was included for the Ponsse Beaver.

Productivity model development

To be able to assess the optimal tree-size range for the two harvester classes, a model that predicts productivity as a function of DBH was developed. The first step of the model development consisted of a visual inspection of the data. Derived machine productivity relative to a DBH class (2.5 cm classes) were plotted as box plots to understand the data ranges and where the median for the productivity for each DBH class was situated. The visual inspection of the data illustrated that

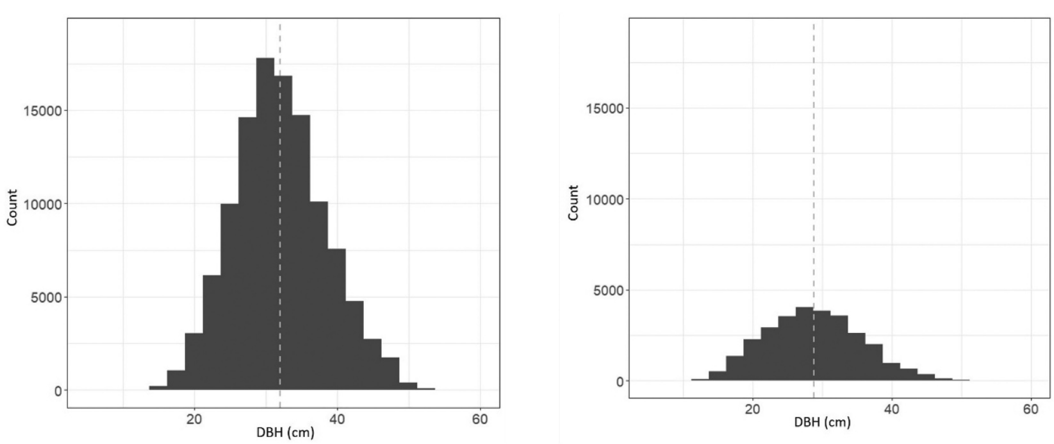

Figure 1. Tree diameter distributions derived from the machine data (mean indicated by the dotted line) for the Bear (left) and the Beaver (right) machines.

Table 1. Tree attributes measured and collected by machines (before data was trimmed at extremes).

Machine	Total observations	Attribute	Mean	Median	SD (±)	SE (Mean)	CV	Minimum	Maximum
All	140,588	DBH (cm)	31.38	31.10	6.62	0.018	0.21	7.30	59.70
		Productivity ($m^3 \cdot PMH^{-1}$)	65.96	63.43	30.56	0.082	0.46	0.82	277.25
		Seconds per tree (s)	54.75	47.00	31.95	0.085	0.58	4.67	300.00
		Stem volume (m^3)	0.92	0.87	0.46	0.001	0.50	0.01	2.50
Bear	111,721	DBH (cm)	32.05	31.10	6.40	6.399	0.20	7.30	59.70
		Productivity ($m^3 \cdot PMH^{-1}$)	70.96	68.97	30.45	30.45	0.43	1.16	277.25
		Seconds per tree (s)	55.13	47.00	31.67	31.67	0.57	4.67	300.00
		Stem volume (m^3)	0.99	0.94	0.45	0.449	0.45	0.01	2.50
Beaver	28,867	DBH (cm)	28.80	28.60	6.81	0.040	0.24	11.00	54.00
		Productivity ($m^3 \cdot PMH^{-1}$)	46.62	0.83	22.13	0.130	0.47	0.83	162.05
		Seconds per tree (s)	53.30	45.00	32.95	0.194	0.62	10.00	300.00
		Stem volume (m^3)	0.64	0.59	0.37	0.002	0.58	0.02	2.45

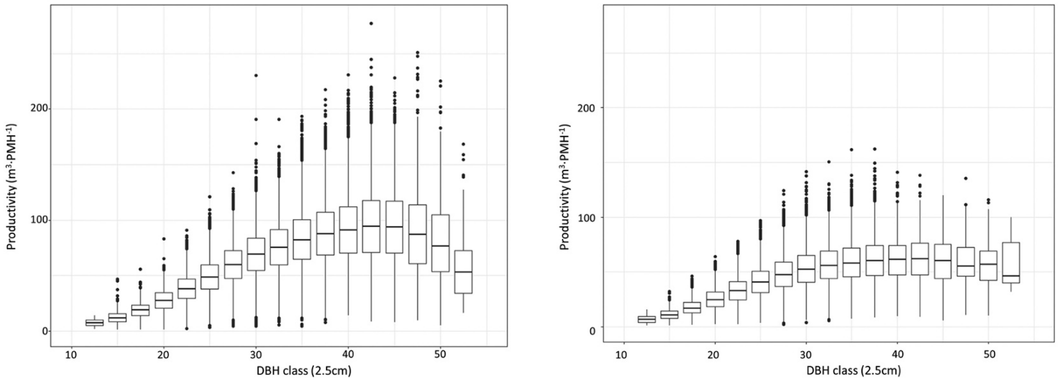

Figure 2. Boxplots of machine productivity per 2.5 cm DBH class for each machine after data cleaning for the Bear (left) and Beaver machines (right).

the relationship between productivity and DBH class was observed to be nonlinear (Figure 2). It is important to note that there were fewer observations in larger trees (> 40 cm DBH) in the Beaver data set.

To fit the observed pattern of the data, we tested a series of selected nonlinear functions with productivity ($m^3{\cdot}PMH^{-1}$) as the dependent variable and DBH (cm) as the predictor variable. After the initial testing it became apparent that a functional form comprising a logistic and an exponential function provided a good fit to the observed patterns in the data both for the Bear and the Beaver (Equation 1).

$$Productivity = \beta_0/((1 + e^{DBH-\beta_1}) \times \beta_2) - e^{DBH \times \beta_3} \quad (1)$$

The form of the function (Equation 1) facilitates the initial rapid increase in productivity for smaller tree sizes followed by a plateau in the mid-range and a decline in productivity as the tree sizes move toward the technical limits of the machine. In Equation 1, the different parameters have the following interpretations: β_0 – sets a factor maximum productivity of each machine, as this should differ between the two machine models, β_1 – sets the rate of initial productivity increase for each machine at smaller tree sizes, in most cases this is rapid, β_2 – shifts the curve toward the left for the logistic regression, and β_3 – indicates the rate of decrease in productivity at large tree sizes, the lower capacity machine should decrease faster than the larger machine model. For the differences between the machine types (Bear and Beaver), the β_0 and β_3 parameters (Equation 1) were allowed to differ between the machine types, since the maximum productivity and rate of productivity decrease should differ between machine models. Conversely, the $\beta_1$and β_2 parameters were the same for both machine types, with the productivity differences in smaller trees being similar (Figure 2) and the shifting parameter being the same for each curve produced.

To account for the hierarchal structure of the data (individual machines, operators, and sites) the model was fitted as a nonlinear mixed effects model with machine fleet ID, harvesting site, and operator ID as a random effect (Equation 2). The parameters in Equation 2 were expanded for β_0 and β_3 for the two machines models.

$$Y_{jsmo} = \beta_0 + (\beta_1 \times M_t) + \alpha_{smo}/((1 + e^{DBH_{jsmo} - \beta_2}) \times \beta_3) - e^{DBH_{jsmo} \times (\beta_4 + \beta_5 \times M_t)} + \varepsilon_{jsmo} \quad (2)$$

Where Y_{jsmo} is the productivity for tree j at site s with machine m and operator o. M_t is a (0,1) indicator variable that indicates if it is a Bear or a Beaver and DBH_{jsmo} is the diameter of tree j at site s with machine m and operator o. $\beta_1 - \beta_5$ are fixed effects and α_{smo} is the random effect implemented on the β_0 parameter accounting for individual machine, operator and site. ε_{jsmo} is the residual error which was modeled using a power of covariate variance function allowing for increasing error variance with the predicted value.

The actual fitting of model 1 was performed using the NLME package (Pinheiro et al. 2017) in R (R Core Team 2017).

Further to this, to derive information key to further analysis of this productivity model, the mean productivity and maximum productivity were calculated. To determine the mean productivity, the integral of the model for each machine was calculated and divided by the difference between the maximum and minimum DBH for that machine model. The maximum productivity was determined by taking the first differential of each of the machine models.

Machine cost analysis

Once the machine productivity models were developed, these results were applied to costing of each of these machines. The machine costing inputs are detailed in terms of general costing and cost sensitivity.

General machine cost

Based on the modeled mean productivity calculated previously, the operating cost ($USD{\cdot}PMH^{-1}$) for the two different harvester size classes was calculated. This machine cost per PMH was developed using market related costs converted from South African rands (ZAR) to US dollars and applied to the single machine model developed by Ackerman et al. (2014b) (Table 2).

Further to the single machine cost per PMH, cost differences between the Bear and Beaver machines were also calculated across the range of DBH classes in the database.

Table 2. Machine cost inputs for each machine.

Cost inputs	Bear		Beaver
Fixed cost inputs			
Machine cost (USD)	379,000		286,355
Attachment cost (USD)	126,333		95,451
Salvage value (base machine)		10 %	
Salvage value (harvesting head)		–	
Expected economic life (base machine)		15,000 h	
Expected economic life (harvesting head)		8,000 h	
Interest rate (%)		7.5 %	
Machine transfers (USD)		7,860	
Machine insurance (USD)		15,160	
Variable cost inputs			
Fuel cost (USD/liter)		0.90	
Fuel consumption (liters/PMH)	20		18
Oil and lubricant cost (%)	20		15
Maintenance and repair (base machine – %)		100%	
Maintenance and repair (harvesting head – %)		100%	
Number of tires (USD)	8		6
Cost per tire (USD)		2,810	
Estimate tire life (USD)		9,000 h	
Consumable – bar cost (USD)		95	
Consumable – bar life		250 h	
Consumable – chain cost (USD)		45	
Consumable – chain life		175 h	
Consumable – sprocket cost (USD)		40	
Consumable – sprocket life		175 h	
Operational inputs			
Working days per annum		248	
Number of shifts		2	
Shift length		8 h	
Machine utilization		85 %	
Expected productivity ($m^3 \cdot PMH^{-1}$)		Determined in results	
Expected tree size (m^3)		0.95	

Note: The USDprices are based on an exchange rate of USD to ZAR of ZAR 17.81 per dollar – 21 March 2020

Cost sensitivity analysis

To further understand cost of capital implications on applying these machines to the sites, a sensitivity analysis to total scheduled hours worked per day (as a combination of shift number, shift length) and interest rate (real) was determined. In this case the machine cost for the Beaver at its mean productivity was subtracted from the machine cost for the Bear at its mean productivity and plotted against the range of the different variables shown in Table 3.

Results

Productivity model development

Results of the analysis conform to convention in that productivity is shown to increase rapidly with increasing tree diameter. Similarly, as the machine productivity increases so does the variability of the productivity estimate (Figure 3). A key result in this is that the plotted productivity vs DBH data follows a trend; a slow initial increase (small trees), followed by a rapid increase in productivity from the smaller diameters to mean tree size, before the productivity begins to taper off, plateaus and then falls away down to the maximum DBH observed for that set of data (Figure 4). A summary of the model parameters for the Ponsse Bear and Ponsse Beaver model are shown in Table 4.

Table 3. Machine cost sensitivity analysis factors.

Sensitivity	Range
Scheduled hours	8, 12, 16, 20, 24
Interest rate (%)	2.5, 7.5, 12.5

The parameters for each of the machines (as described previously) are all significantly different ($p < 0.05$). As expected, these modeled parameters indicate that the larger (Bear) machine has a greater maximum productivity (parameter β_0), the Beaver's productivity peaks earlier. The rate of initial increase in productivity remains constant (parameter β_2) along with the shifting parameter (parameter β_3). The last parameter, the rate of productivity decrease is greater in the smaller (Beaver) than the larger machine. This parameter decreases the machines modeled productivity (for the Beaver) at an exponentially greater rate after the productivity peak. These estimated parameters fit what would be expected for the machines operating in these conditions, especially that the smaller machine would be able to operate effectively in larger trees but that the productivity would decrease more rapidly. The model is visually described in Figure 3.

These modeled productivities show a clear difference between the productivity of the two machines, the Bear being more productive throughout the DBH range than the Beaver, particularly in the larger diameters. The peaks

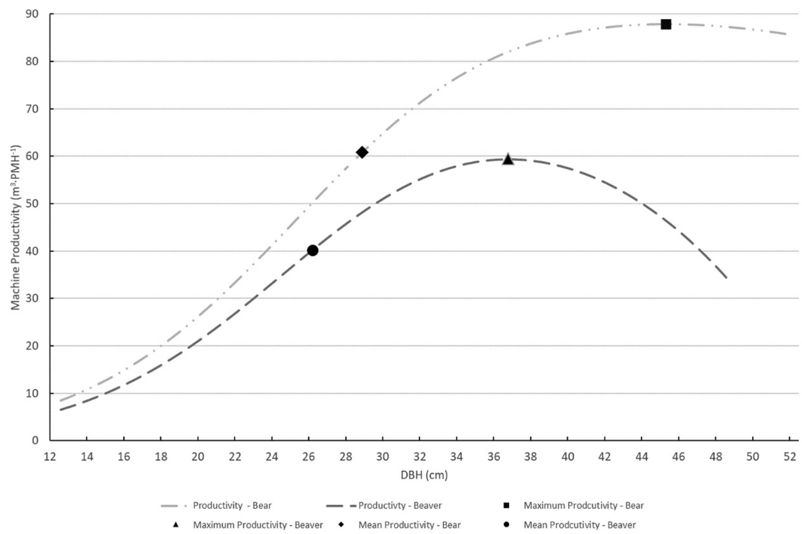

Figure 3. Line plots of the relationship between modeled machine productivity and DBH for the large capacity Bear (dotted) and smaller capacity Beaver (dashed). The markers indicate the point of mean and maximum productivity for each model.

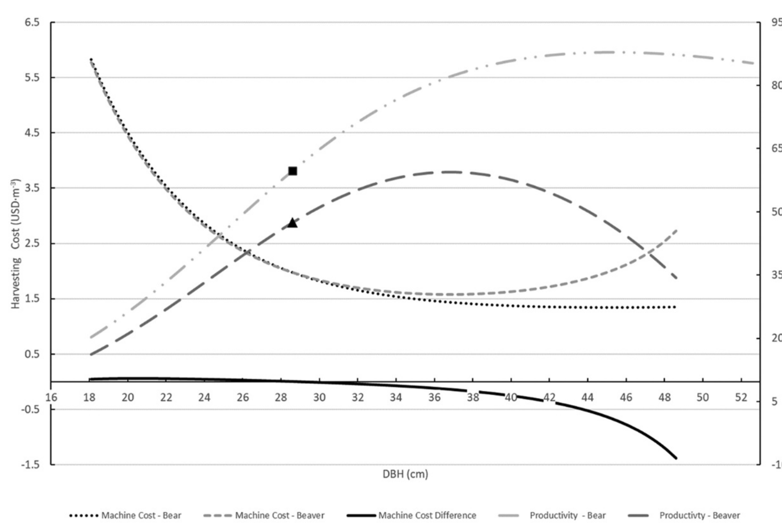

Figure 4. Line plots of the relationship between modeled machine productivity and DBH of the two machines, the machine cost, and the cost difference between the machines. The mid-points of the DBH ranges for the Bear and the Beaver where the cost difference is ~USD 0.00 are marked on the respective productivity curves.

Table 4. Nonlinear Mixed Effects model results.

Fixed effect	Estimate	Std Error	DF	*t*-value	*p*-value
β_0	102.10662	1.958218	140,459	52.14263	<0.001 ***
β_1	92.52183	3.30068	140,459	−2.90388	0.0037 **
β_2	25.48385	0.081035	140,459	314.481	<0.001 ***
β_3	−0.16874	0.001262	140,459	−133.69438	<0.001 ***
β_4	0.05249	0.002216	140,459	23.69001	<0.001 ***
β_5	0.08296	0.001974	140,459	15.4366	<0.001 ***

Signif. codes: *** 0.001; ** 0.01; *0.05; 0.1

(before decline) indicate that the Bear has much greater capacity remaining for larger trees. Even with fewer tree observations in the larger trees for the Beaver data set, the trend in rapid decrease in machine productivity is what would be expected by this machine.

Based on the machine productivity models the calculus integration and differentiation determined the modeled mean machine productivities and DBH value for the maximum productivity found (Table 5). The maximum productivity rates found for the differentiated functions are illustrated by the point markers in curves in Figure 4.

These data were further applied in the machine cost calculations of the two machines.

Machine cost analysis

General machine cost

Using the calculus integration of mean productivity from the NLME model, the cost for the machines was calculated. The results of these calculations are indicated in Table 6.

Using the mean productivities calculated though integration, a summary of the respective cost per PMH and per m^3 are shown in Table 7.

Table 5. Summary information related to integrated mean productivity and first differential maximum productivity of each model.

Machine	Mean productivity ($m^3 \cdot PMH^{-1}$)	DBH at maximum productivity (cm)	Maximum productivity ($m^3 \cdot PMH^{-1}$)
Bear	60.8	45.3	87.8
Beaver	40.2	36.8	59.4

Table 6. Machine cost calculation outputs from the general machine costing.

	Costing Outputs							
	Fixed costs							
	Annual		Monthly		PMH		Cost·m^{-3}	
Machine	**Bear**	**Beaver**	**Bear**	**Beaver**	**Bear**	**Beaver**	**Bear**	**Beaver**
Depreciation – base machine (USD)	76,697	57,949	6,391	4,829	22.74	17.18	0.37	0.43
Depreciation – attachment (USD)	53,262	40,242	4,438	3,353	15.79	11.93	0.26	0.30
Total Depreciation	129,959	98,191	10,829	8,182	38.53	29.11	0.63	0.72
Interest on average annual investment – base machine (USD)	18,510	13,985	1,542	1,165	5.49	4.15	0.09	0.10
Interest on average annual investment – attachment (USD)	6,735	5,088	561	424	1.99	1.51	0.03	0.04
Interest Total (USD)	25,245	19,073	2,103	1,589	7.48	5.65	0.12	0.14
Insurance (USD)	7,860	7860	655	655	2.33	2.33	0.04	0.06
Machine Transfers (USD)	15,160	15,160	1,263	1,263	4.49	4.49	0.07	0.11
Total Fixed Costs (USD)	178,224	140,284	14,850	11,689	52.84	41.59	0.87	1.03
	Variable costs							
	Annual		**Monthly**		**PMH**		**Cost·m^{-3}**	
Machine	**Bear**	**Beaver**	**Bear**	**Beaver**	**Bear**	**Beaver**	**Bear**	**Beaver**
Fuel (USD)	60,710	54,639	5,059	4,553	18.00	16.20	0.30	0.40
Oil and lubricants (USD)	12,142	8,196	1,011	683	3.60	2.43	0.06	0.06
Maintenance and repairs (base machine) (USD)	85,219	64,388	7,101	5,366	25.27	19.09	0.42	0.47
Maintenance and repairs (attachment) (USD)	53,261	40,242	4,438	3,353	15.79	11.93	0.26	0.30
Fuel, Maintenance and Repairs – Total (USD)	211,332	167,465	17,609	13,955	62.66	49.65	1.04	1.23
Tyres and other main running gear (USD)	4,776	4,776	398	398	1.42	1.42	0.02	0.04
Consumable – bar (USD)	1,281	1,282	106	107	0.38	0.38	0.01	0.01
Consumable – chain (USD)	867	867	72	72	0.26	0.26	0.00[a]	0.01
Consumable – sprocket (USD)	770	771	64	64	0.23	0.23	0.00[a]	0.01
Total Variable Costs (USD)	219,026	175,161	18,249	14,596	64.95	51.93	1.07	1.29
Total cost (USD)	397,250	315,445	33,099	26,285	117.79	93.53	1.94	2.32

[a]Note: The values indicated USD 0.01 occurred as the cost of these items were very low in relation to the machine productivity

Table 7. Cost summary information (USD) related to the mean productivity for each machine.

Machine	Mean productivity ($m^3 \cdot PMH^{-1}$)	Cost·PMH^{-1}	Cost·m^{-3}
Bear	60.8	$117.79	$1.94
Beaver	40.2	$93.53	$2.32

Based on the mean productivities and costs indicated in Table 6, plotting the cost relationship over the DBH and the related cost difference between the two machines are shown in Figure 4.

The figure shows that the Ponsse Beaver is slightly less expensive to run in smaller tree sizes compared with the Ponsse Bear. There is a phase where the net production cost between the Bear and the Beaver is close to zero, this range indicated by the cost difference line as lying approximately between 26.0 cm and 31.0 cm DBH (or close to absolute zero at 29.0 cm DBH). The net sum of the differences in this range are less than USD 0.01·m^{-3} . Beyond that, the economic advantage of the larger Bear increases with increasing diameter.

Cost sensitivity analysis

A major concern in machine investment is whether the depreciation component remains manageable if the cost of capital or level of utilization changes significantly. Therefore, in addition to comparing the two machines over a range of tree sizes, a sensitivity analysis of their cost differences at their mean productivity rates, but under differing interest rates and number of scheduled machine hours per year (number of shifts per day and shift length) was done to illustrate the robustness of the results (Figure 5).

The relative specific cost between machine sizes varies by an additional approximately 17% in the worst case (eight SMHs per day, and interest rate of 12.5%) (Figure 5). The figure further indicates how this cost difference is sensitive to the number of scheduled machine hours as well as the interest rate. This is

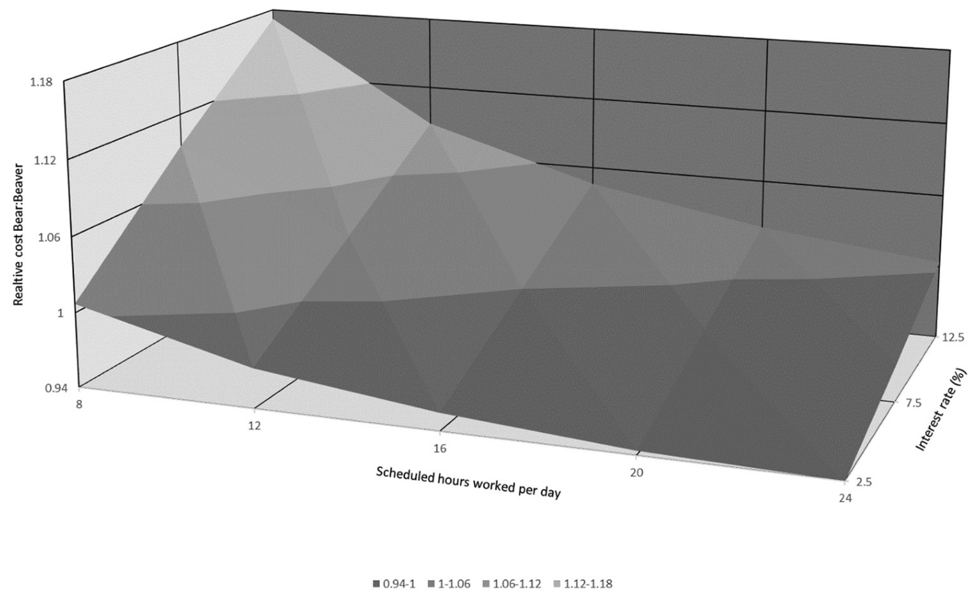

Figure 5. An area graph describing the normalized cost difference between the specific cost of the Ponsse Beaver and the Ponsse Bear for changing interest rate and total scheduled hours per day.

particularly evident in areas where the interest is high with low working hours and at the other extreme, low interests and high working hours.

Discussion

StanForD-derived data

The use of large follow-up data sets limits the control researchers have on measuring and monitoring the work object, in this case the tree being harvested. It also limits the extent to which one can accurately control outliers and errors in these kinds of datasets. Typically, analysis of short-term machine productivity involves a limited number of hours observing the machine on a controlled set of trees, measured, and marked for evaluation (Ackerman et al. 2014a). This study used a set of data that relied solely on the machine calibrated measurements. On the positive side, this approach allowed the machine productivity to be evaluated over an extended period and evaluate big data trends, similar approaches have been followed by Eriksson and Lindroos (2014); Lu et al. (2018); Olivera and Visser (2016) and Olivera et al. (2016).

For this study, approaches from some of the abovementioned studies were used as well as systematic statistical outlier removal was done. In the first wave of data cleaning, many observations were removed, which is typical in the analysis of follow-up data (Strandgard et al. 2013; Olivera et al. 2016). Further, bounding of the data enabled the tree size classes to have a greater number of observations and further remove trees that would either be too big or too small to fit within the characteristic tree sizes typical for clear-felling in the study area.

Machine productivity model

It appears that the use of nonlinear mixed effects to model machine productivity is relatively new in forest operations, but is more widely used in modeling other processes in forestry (Erasmus et al. 2018). The conventional modeling approaches are to use generalized linear models or match logarithmic functions to these types of data. More recently the use of linear mixed effects models has been demonstrated by Olivera et al. (2016) to model machine productivity in harvesting different tree species and operators against the machine measured tree DBH, although in this case these data were presented as a logarithmic function and linearly transformed. The scope for modeling this large data set is however expanding into the realm of machine learning and other advanced modeling techniques (Liski et al. 2020). Other statistical methods to NLME were possible, however, the hierarchical structure of the data justified the use of a mixed effects model where normality of errors were assessed and model errors were modeled using a power function.

The model produced in this paper sought to evaluate the productivity difference between two different size machine models on a large follow-up data set. The study revealed good interactions between the machine productivity for the two different machine models against machine measured DBH, the relationship between productivity and DBH is the widely accepted relationship in modeling these data (Visser et al. 2009; Alam et al. 2014).

In the results of the modeling, the data presented an additive model incorporating a logistic and exponential function. This model was parameterized to encapsulate the differences in maximum machine productivity and the rate of machine productivity decline, as these factors are expected to be unique for two different capacity machines based on tree sizes. For this reason, the aim for forest operations researchers is to identify the effect tree size has on machine productivity when the size of the tree stretches the technical limits of the machine. The shape of this function is present in investigations of a similar nature by Visser and Spinelli (2012) and Visser et al. (2009), further supporting the development of this predictive model. In fitting this model, the study further explores the theoretical machine capability "sweet spot" for the two machine models investigated in this study.

The increase in data variability or data fanning, as illustrated in Figure 2, is often visible in the plotting of big data sets. In some cases, this can be caused by noise created by data being recorded incorrectly, but also as the machine moves beyond its capabilities (tree size, boom reach, etc.) the range in measured productivities change. This anomaly has been explained by a reduction in machine performance (Ramantswana et al. 2013) and visually this phenomenon is seen in Olivera et al. (2016). Linearizing these data sets is often done to reduce this variance and improve the fit of the data when modeling.

The results from the model show a predicted mean productivity of 60.8 $m^3{\cdot}PMH^{-1}$ and 40.2 $m^3{\cdot}PMH^{-1}$ for the Bear (larger) and the Beaver (smaller) machine models, respectively. These values are within range of the values presented by Wenhold et al. (2020) of between 40 and 70 $m^3{\cdot}PMH^{-1}$ for these machines and somewhat higher than those found by Williams and Ackerman (2016) of 11– 63 $m^3{\cdot}PMH^{-1}$. Both these studies were conducted in similar tree sizes and geographic areas. Where Wenhold (2020) used long-term machine derived data, only using the Bear machine data for clear-felling, and Williams (2016) analyzed observational time study data (500 cycles) of a smaller average tree size. The results presented in this study, therefore, do appear within range of those expected for these conditions, even though a different modeling approach was used.

The difference between machine models was chosen as the main effect to investigate, when selecting variables for the NLME analysis. Other studies have shown that there are substantial differences between the productivity between small and large capacity machines (Ledoux and Huyler 2001; Eriksson and Lindroos 2014). For this reason, using the other factors as random effects (operator, machine fleet name and site) is justified. Operator is a major driver of machine productivity (Nurminen et al. 2006; Ramantswana et al. 2013; Alam et al. 2014; Wenhold et al. 2020), and in a similar sense so is the site (Saremi et al. 2014) and the different machine (company fleet name). Fleet name was included as it is believed there is an interaction between the operator and the different machines these operators use during time at the job site. The study included eight operators that were employed and trained by the grower company since the transition to CTL harvesting (18 months) as described by Wenhold et al. (2020).

Using the machine type as an evaluation criterion did enable detailed productivity-related machine costing and cost sensitivity analysis.

Machine cost calculations

The assumption of a 15,000 h economic lifetime was lower than the 19,000 h used by Diniz et al. (2020) under similar conditions, and the 63,000 h maximum useful lifetime suggested by Cantú et al. (2017) in a boreal setting. A lower anticipated machine lifetime increases the hourly depreciation cost component, theoretically favoring the machine with the lower purchase price (Beaver). The assumption of equal expected economic lifetimes is based on the machines working within their design specifications. The expected economic lifetime of the harvesting head was conservatively estimated at 8000 h with no residual value, equating to 520,000 m^3 on the Ponsse Bear and H8 head and 360,000 m^3 on the Ponsse Beaver and H6 head. In retrospect, it might have been more accurate to fix equal volumes or number of trees harvested and differentiate the expected useful lifetimes of the harvesting heads.

The fixed PMH costs of the Bear were USD 52.81 and of the Beaver, USD 41.39 while the corresponding total PMH costs were USD 117.79 and USD 93.53, respectively. Machine costs did not include operator costs and social on-costs, enterprise administration costs or any profit margin to the machine owner. Further, the South African currency (ZAR) is currently considered by The Economist's "Big Mac index" to be undervalued by 62% against the US dollar (Wasserman 2020), implying that any direct exchange rate based conversions underrepresent the real USD equivalent cost. Regardless of this anomaly, the cost relationships between the machine sizes presented in this paper remain sound.

Machine cost difference

When comparing the machine costs over the range of tree sizes these machines operated in, the widely established relationship of high cost for small tree sizes reducing to an optimum tree size and increasing once again as the trees exceeded the machine size capacity was observed (Visser and Spinelli 2011; Alam et al. 2012; Spinelli and Magagnotti 2013). The interesting part is the comparison of two different size machines over the tree size range. The smaller machines are more cost effective in small tree sizes, and the opposite is true for larger trees with larger machines becoming more cost effective. Even though the differences in these costs are small in the smaller tree sizes, they become more apparent in larger trees where the larger machine is much more productive. This appears to indicate an area where machine choice makes very little difference for a particular tree size, in terms of cost. The range of tree sizes where the net cost difference is close to zero, roughly between 26 cm and 31 cm DBH, indicate a cutoff where smaller machines could be applied to stands more effectively than larger machines. However, the analysis is not simple as it is based on mean tree sizes while the distribution around these means is often not known beforehand. This area represents relatively small tree sizes compared to that expected from clear-felling plantation forestry pine sawtimber regimes, but fits well for thinnings (Kotze and du Toit 2012). However, in this study, only clear-felling was observed and the thinning data from the Beaver was precluded. Internationally there has been a trend toward shorter rotations and thus smaller trees (McEwan et al. 2020), implying that in the future the application of large machines may become less common in plantation forestry. In contrast, vertically integrated corporates might weight productivity higher than the specific cost and select the machine size that maximizes the volume harvested per day in supplying high demand mills. Where the opposite is true for small timber harvesting enterprises where incurring the capital cost (or being able to secure capital) for a large machine working in smaller trees is often a challenge.

However, these presented results do indicate the mean and maximum productivities, as well as the zone of similar production costs between two harvester machine sizes.

Cost sensitivity

The capital outlay when choosing to invest in advanced machines is one of the biggest drivers of the depreciation component, especially where interest rates are high. To compensate for this, machine owners opt to run their machines for as many hours as possible, often scheduling up to 24 h a day in multiple shifts (Steyn et al. 2011; Diniz et al. 2020), While the depreciation is reduced, this practice is often associated with higher maintenance and repair costs, as well as operator shortages (Pasicott and Murphy 2013).

There was a considerable difference (32%) in purchase price between the Ponsse Bear (USD 505,333) and Ponsse Beaver (USD 381,806). However, the production cost sensitivity analysis (Figure 5) shows relatively small differences even in unfavorable conditions (high interest rates and minimal machine hours) for the higher priced Bear. The overall relative cost difference range is ~23%, representing a real cost difference of USD 1.15 and USD 0.92 respectively. Interestingly, the higher productivity of the larger machine largely outweighs the penalizing influence of high cost of capital (interest) and low degree of utilization.

Conclusion

Productivity maxima for the two different harvester sizes were clearly distinguishable at 36.8 cm DBH for the smaller Ponsse Beaver and 45.3 cm trees for the larger Ponsse Bear. At maximum, the Ponsse Beaver showed a productivity of 59.4 m^3 PMH^{-1} while the Bear had a productivity of 87.8 m^3 PMH^{-1}. Given that terrain conditions in the area are generally good to excellent and the trees have good form, good size, are planted in rows and pruned to 5–7 m, these productivity figures likely approach the upper productivity frontier for CTL harvesters internationally. Interestingly, the lower capital cost and therewith depreciation charge almost completely compensated for the significantly lower productivity obtained on the Ponsse Beaver, and both machine sizes, therefore, harvested timber at an almost identical cost. The study did not investigate whether the relatively large tree size corresponding to the highest productivity level for the smaller Ponsse Beaver resulted in higher maintenance and repair costs for those machines. Such information would be useful in establishing clearer "operational boundaries" between machine models.

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