



Understanding the influence of tree size distribution on the CTL harvesting productivity of two different size harvesting machines

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Received: 15 January 2024 / Revised: 29 February 2024 / Accepted: 9 March 2024
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Abstract

Tree size is one of the major factors that determines harvester productivity and is heavily influenced by forest managerial activities. Stand silvicultural management can lead to managing tree size, the distribution of tree size, and tree height amongst others. Understanding the effect of tree size distribution on harvesting productivity is central for optimizing management of operations. To investigate the effects of tree size distribution on harvester productivity, productivity functions for a medium and larger-sized harvester were applied to harvester derived tree size distributions from 35 clearfelled pine stands. These functions were applied to a normal distribution of trees covering the same tree size ranges. Productivity differences were analysed on a stand-by-stand basis. Results showed that for the larger harvester, productivity rates remained constant (67.1 vs. 67.6 m³·PMH⁻¹) indicating relatively little sensitivity to variations in tree size distributions. Although the standard deviation (SD) halved from 11.6 to 5.6 in the case of the uniform tree distribution. The smaller harvester productivity decreased by 15% from 47.3 to 40.1 m³·PMH⁻¹ and the coefficient of variation (CV) by 6% in the same transition to a uniform distribution. Further investigation was done on more skewed tree size distributions, a family of nine Weibull distributions was generated, representing combinations of three mean DBH classes (25 cm, 30 cm, and 35 cm) and three levels of CV (15%, 20%, 25%), for each DBH class. Results clearly indicate that different distribution shapes have different effects on different machine sizes, and that a low CV correlates to a higher productivity in larger tree sizes. A more uniform tree size distribution also provides more predictable results (lower CV), which would promote machine scheduling and result in fewer discrepancies on production rates.

Keywords Non-symmetrical Tree distributions · OBC · Weighted mean productivity · Weibull · Clearfelling

Communicated by Eric R. Labelle.

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Introduction

Basic background to industrial plantation forestry and uniformity

Timber harvesting technology in plantation forestry has transitioned towards highly productive machine solutions (McEwan et al. 2020). The worldwide increase in industrial plantation forestry in the last few decades (Keenan et al. 2015), has enabled the widespread application of these mechanised systems on uniform sites with uniform tree sizes. These sites have been managed through silvicultural interventions; planting the best genetics, tending, pruning and thinning to improve uniformity and overall plantation yield (Little and Rolando 2001; Rolando et al. 2003; De Moraes Gonçalves et al. 2004). This does allow for some predictability of future tree volumes and sizes as well as a prior knowledge of the kind of harvesting technologies

to apply (Ledoux and Huyler 2001). This differs somewhat from what can be expected in natural or managed natural forests with uneven age structures and natural ingrowth (Eriksson and Lindroos 2014). However, despite being relatively uniform, managed plantations still contain a level of inter-tree variability (Saremi et al. 2014). Given that mechanised systems are expected to perform at very high rates under plantation forestry conditions, even smaller variation in tree sizes and properties might have a disproportionately large influence on overall performance (Rossit et al. 2019).

Tree distributions and uniformity

Industrial saw-timber plantation management prescriptions are aimed at producing uniform sized trees through good establishment techniques and silvicultural interventions that are timeous and result in evenly spaced trees (Sterba and Amateis 1998; De Moraes Gonçalves et al. 2004; Ackerman et al. 2013). In the case of saw-timber production, thinning practices influence the quality of the logs produced at end of rotation for conversion into sawmill-ready merchandised logs. Thinnings from below are practiced in industrial plantations like those in South Africa (von Gadow and Bredenkamp 1992; Ackerman et al. 2013). This practice aims to ensure trees of poor form and those that are smaller than desired are removed while balancing the requirement for even tree spacing. Even with these silvicultural and harvesting interventions, stand heterogeneity does still occur, often due to intra-stand variability i.e., slope, soil differences and the presence of rocks limiting soil depth (Olivera and Visser 2016), delayed replanting of dead trees (blanking) at establishment (Pallett 2005) and mismatched thinning practices (Ackerman et al. 2013). These factors lead to the distributions of tree sizes with greater variability or skewness and with a high coefficient of variation (CV). This in turn can lead to reduced harvesting productivity (Pettersson 2017). In this study, we investigate how stand heterogeneity, represented as variable levels of CV of diameters, affects cut to length (CTL) harvesting productivity where the trees are felled and processed into log lengths for extraction by a forwarder to roadside.

Productivity of machines in target tree dimensions

When the investment decision is made to purchase cut-to-length (CTL) harvesters, which require a high capital outlay, the enterprise needs to ensure that they will be applied to the optimal timber size classes to be most effective (Pettersson 2017; Ackerman et al. 2022). Studies have also shown that beyond a certain tree size the variability in productivity between machines tends to increase (Olivera et al. 2016; Pettersson 2017; Ackerman et al. 2022) and a certain

machine size class has a ‘sweet spot’ or optimum productivity range with regards to the tree size it is applied to (Visser et al. 2009; Ackerman et al. 2022; Louis et al. 2022). This is where the machine can be expected to operate optimally based on its technical specifications.

Uncertainties in terms of tree size distribution can lead to an enterprise purchasing a larger machine than needed to account for unforeseen variability within the stands (Diniz and Sessions 2020). Traditional tree size related productivity relationships are common, also the notion that these curves reach a point where the productivity levels out, mainly based on the size of the machine. The rate of change in productivity, or marginal productivity has been found to be greater in smaller trees than in larger trees (Eriksson and Lindroos 2014) while in Ackerman et al. (2022) the intermediate area showed the greatest rate of change. However, when the tree size becomes too large for the machine to handle, the productivity of the machine drops off, similar to the trends shown in Visser et al. (2009), Alam et al. (2014) and Ackerman et al. (2022). Productivity functions, whether linear or non-linear, always reflect a rate of productivity for a given interval of tree size. Basing a stand-level productivity estimate on such a value implies an underlying assumption that the tree sizes are normally distributed, and the productivity estimate is given for the mean of that distribution. It also assumes that the expected productivity rate for the trees at the upper end of the distribution precisely compensate for the productivity rate of the trees at the lower end of the distribution. However, productivity functions are seldom linear and, in reality, tree size distributions seldom normal (Forrester 2021).

Knowing more about how non-normal tree size distributions influence machine productivity at a stand level could contribute to more accurate operations planning and assortment forecasting. However, prior estimates of diameter distributions would be required if they are to be used in prediction. These distributions can be gathered through manual measurements or remote sensing. Aerial laser scanning (ALS) was proven to be useful in generating such distributions in coniferous forests (Gobakken and Næsset 2004; Rätty et al. 2021). Productivity models can be developed on the basis of tree distribution data collected from the on-board computer and StanForD data library (Kemmerer and Labelle 2021), or further enhanced by combining it with the aforementioned ALS data, as demonstrated by Söderberg et al. (2021). To investigate the extent to which variability in tree size affects harvester productivity, Pettersson (2017) analysed data from 383 final felling operations (including 10 harvesters and 670 000 m³) and 112 thinning operations (including eight harvesters and 82 000 m³). This study found that the greater the variation of diameter distribution the lower the harvesting productivity.

Problem statement

In current operational harvesting planning, it is practice predicting and manage harvesting productivity on enumerated tree data. These data are based on a sample plot-based measurements of trees distributed throughout the stand (usually 5% of the area of the stand) to ensure that the variability of the tree sizes is taken into account (von Gadow and Bredenkamp 1992). These data yield mean tree size and a sample-based tree distribution. Often only the mean tree size data is used as the standard predictor of machine productivity for the stand. This can lead to under or over estimation of productivity in cases where tree sizes are not normally distributed around a given mean, standard deviation (SD) and coefficient of variation (CV) derived from the SD and DBH.

Objectives

The objectives of the study were to:

- Investigate the effect of two sizes of CTL harvesting machines; on-board computer (OBC) derived data on weighted mean productivity.
- Derive mean tree size and CV trends based on these harvester data to generate a set of skewed Weibull tree distributions to test the differences in weighted mean machine productivity across these distributions for the two machines sizes.

Materials and methods

Study site

The study consisted of 35 clearfell stands (~300 ha) located in the Mpumalanga Highveld of South Africa, roughly at 26.24° S and 30.48° E and at an altitude of about 1750 m asl. The sites were ideally suited for mechanised CTL harvesting with the terrain being level even (Erasmus 1994), with evenly spaced, thinned, and pruned *Pinus patula* trees of approximately 0.9 m³ on average.

Data

Two datasets were used in this study: (1) Machine derived data directly derived from harvesting machine OBCs, and (2) a simulated dataset generated to investigate the effect of different types of tree size distributions on harvesting productivity. The simulated data was created by applying

Weibull functions parametrised from the means and coefficient of variation (CV) groups from the machine derived data.

Machine derived data

Harvester OBC data from four Ponsse CTL harvesting machines (two Ponsse Bears and two Ponsse Beavers) working in *Pinus patula* sawtimber stands were collected. The machines studied were two of the larger, eight-wheeled Ponsse Bear (24.5t, ~260 kW) and two of the smaller six-wheeled Ponsse Beaver (17.5t, ~150 kW) machines. The machine types were not compared, however, evaluated based on tree distributions.

Harvester data was comprised of approximately 12 months of machine work based individual tree data from each of the four machines. The data set comprised of approximately 140 000 individual tree records. These trees were gathered from the OBC's of both the Beaver and Bear machine types harvested in the study area. These tree data were recorded using the StanForD classic protocol described by Arlinger et al. (2012). These data received a basic cleaning and were processed and analysed to produce machine type specific productivity models, detailed by Ackerman et al. (2022), these productivity functions were applied in this study.

Diameter distributions for each of 30 stands in the OBC data were developed using DBH bins of 2.5 cm's. These DBH distributions were bounded between 12.5 and 52.5 cm for the purpose of the study, since the majority of trees were found between these diameters. Mean tree volumes were calculated based on the DBH class midpoint and the mean height of a tree for that diameter. The mean height was modelled based on forest management enumeration data from sample stands in the study area, for each DBH class. Standing tree volume was determined using these metrics, and then applied to a parametrised 'compatible volume function for the Max and Burkhart taper function' detailed in Bredenkamp (2012), for the target species, *P. patula*.

The first step was to develop a k-factor (pseudo-form factor) for the species from the regression coefficients (Eq. 1).

$$k - factor = b_{1/3} + b_{0/2} - (b_0 + b_1) + b_{2/3} \times (b_4^3) + b_{3/3} \times (b_5^3) \quad (1)$$

The regression coefficients for this equation were as follows:

$$\begin{aligned} b_0 &= -3.268, \quad b_1 = 1.502, \quad b_2 = -1.783, \quad b_3 \\ &= 23.772, \quad b_4 = 0.731, \quad b_5 = 0.094 \end{aligned}$$

The k-factor was calculated as 0.407280515 and used to predict the tree volume based on tree DBH and height for each DBH class (Eq. 2).

$$\begin{aligned} \text{Tree volume} &= (\pi/40,000) \times k \\ &\quad - \text{factor} \times (\text{DBH}^2) \times \text{tree height} \end{aligned} \quad (2)$$

The machine productivity models produced by Ackerman et al. (2022) for the two machine sizes were applied to these data to determine the expected productivity for each of the DBH classes and the overall marginal productivity per stand. The marginal productivity is the rate of change in volume over time for each DBH class based on the productivity model. The general productivity model with the associated parameters is given in Eq. 3.

$$Y_{jsmo} = b_0 + (b_1 \times M_t) + \alpha_{smo} / ((1 + e^{DBH_{jsmo} - b_2}) \times b_3) - e^{DBH_{jsmo} \times (b_4 + b_5 \times M_t)} + \varepsilon_{jsmo} \quad (3)$$

Where parameters : $b_0 = 102.1066$, $b_1 = 92.5218$, $b_2 = 25.4839$, $b_3 = -0.1687$, $b_4 = 0.0525$, $b_5 = 0.0830$

To describe the variables, 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 modelled using a power of covariate variance function allowing increasing error variance with the predicted value.

The weighted mean productivity is related to the quotient of the total volume of timber in the distribution and the total time taken to harvest that volume.

To determine the weighted mean productivity of a given stand, the following steps were followed: The total volume for each DBH class was determined by calculating the product of the mean tree volume and the number of trees per DBH class. Using these values, the cumulative volume for the stand was calculated. The time taken to harvest the volume in each DBH class was then determined by calculating the quotient of the total volume per class and the expected machine productivity (marginal productivity). Using these values, the cumulative harvesting time for the stand was then determined. The volume weighted mean productivity for the stand was then determined for each distribution using cumulative time and cumulative volume.

This method was applied to all the stands in the data set. Further descriptive data pertaining to DBH, CV of DBH, and marginal productivity were calculated. The CV was used to classify the stands into DBH – CV groups.

Simulated stand structures

To test the productivity trends seen in the OBC data over a wider range of tree size distributions, a 3×3 matrix of stand mean diameters (25, 30, 35 cm) and their interaction with three levels of CV was generated. Firstly, the SD for the OBC data was plotted (Fig. 1) and a simplified grouping by DBH class was made at CV's of 15%, 20%, and 25%.

There are distinct groupings concerning the mean DBH and related CV, derived from the SD, for that DBH (roughly in the mid-point of the groups). These groupings are both visual and also fall within 5% ranges of each other. For the study three data groupings were identified centring around; a DBH 30 cm – CV 20% as well as two others one lower and one higher at DBH 25 cm – CV 15% and DBH 35 cm – CV 25%. The original data, without grouping, shows a general trend of increasing CV with increasing tree size. These were expanded further to incorporate two other points, again one higher and one lower than the mid-points (Table 1). This grouping allowed a matrix of options to test multiple scenarios with varied CV of DBH at particular DBH points.

$$f(x, \alpha, \beta) = \frac{\alpha}{\beta^\alpha} x^{\alpha-1} e^{-(x/\beta)^\alpha} \quad (4)$$

with mean (Eq. 5)

$$\mu = \frac{\beta}{\alpha} \Gamma\left(\frac{1}{\alpha}\right) \quad (5)$$

and variance (Eq. 6)

$$\sigma^2 = \frac{\beta^2}{\alpha} \left\{ 2\Gamma\left(\frac{2}{\alpha}\right) - \frac{1}{\alpha} \left[\Gamma\left(\frac{1}{\alpha}\right) \right]^2 \right\} \quad (6)$$

To relate the existing data with a Weibull distribution, the previous two equations are rearranged, as follows (Eqs. 7 and 8):

$$\beta = \frac{\mu}{\Gamma\left(1 + \frac{1}{\alpha}\right)} \quad (7)$$

and

$$\sigma^2 = \beta^2 \left(\Gamma\left(1 + \frac{2}{\alpha}\right) - \left(\Gamma\left(1 + \frac{1}{\alpha}\right) \right)^2 \right) \quad (8)$$

The gamma function is defined as (Eq. 9)

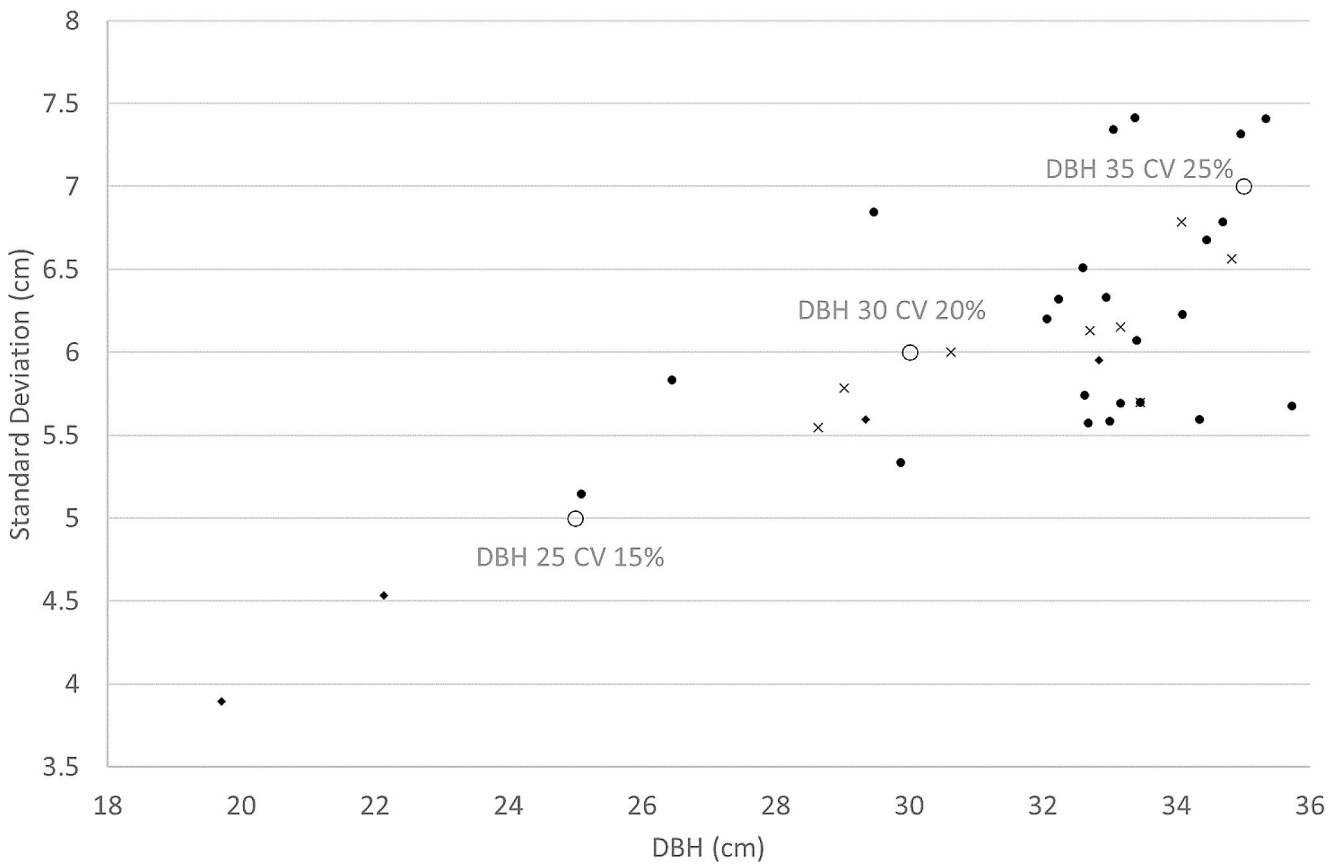


Fig. 1 Plot of the SD (cm) vs. DBH (cm) for each of the machine derived stands. Stands are grouped (by marker) according to mean DBH classes 25, 30, and 35 cm. The empty circles indicate the categories used in generating alternatives for a CV % related to DBH

Table 1 Stand parameters used in generating tree size distributions. The values indicate the CV (SD in cm) range used for each DBH class

	DBH (cm)		
Coefficient of variation (% of SD/DBH)	25	30	35
15	3.75	4.5	5.25
20	5	6	7
25	6.25	7.5	8.75

The mean and variance of the DBH data were then used to develop related Weibull distributions. Depending on the shape and scale parameters used, Weibull distributions can be left skewed, right skewed, or approximate normal distributions and are therefore useful in describing diameter distributions (Gobakken and Næsset 2004). The Weibull density function with parameters α (shape) and β (scale) is (Eq. 4):

$$\Gamma(z) = \int_0^{\infty} z^{z-1} e^{-x} dx \tag{9}$$

Mean value and variance estimates from the data can be used to solve for α and β using Eqs. 7 and 8. The following equation (Eq. 10) results after combining these.

$$\frac{\alpha^2}{\mu^2} - \frac{\Gamma(1 + \frac{2}{\alpha})}{\Gamma(1 + \frac{21}{\alpha})^2} + 1 = 0 \tag{10}$$

The value of α in Eq. 10 can be determined through a numerical method; in this study, it was solved using the Solver add-in of Microsoft Excel. The values of μ and σ were estimated from the data. Once α is known, it can be substituted into Eq. 7 to determine the value for β (Table 2). For each parametrised Weibull density function, a tree size distribution was generated. The productivity function (Eq. 2) was run on each tree size distribution for the Bear and Beaver respectively. Based on these distributions a weighted mean productivity for each of the machine size was calculated. The point at which the machine productivity reached its maximum was then determined, through calculating the first derivative of the weighted mean productivity curve for each size machine. The marginal productivity function (Eq. 3) was then applied to each of these nine tree size distribution scenarios. For comparative purposes, and to illustrate the consequences of assuming stands are normally distributed, the weighted mean productivity for a normal distribution with the same mean and SD was determined.

Table 2 Machine derived stand data with associated weighted mean and marginal productivities. (CV% is calculated as SD/Mean)

Stand	Stems	DBH	Mean (cm)	10th percentile (cm)	90th percentile (cm)	SD (cm)	CV %	Weighted Mean productivity (m ³ ·PMH ⁻¹)		Marginal productivity (m ³ ·PMH ⁻¹)	
								Bear	Beaver	Bear	Beaver
A15	1593		19.71	15.75	41.75	3.90	20%	26.50	21.16	87.37	51.93
A13	1807		22.14	15.50	39.50	4.54	21%	34.96	27.92	80.09	47.60
F22a	3486		25.10	16.25	46.25	5.15	21%	45.81	36.06	64.08	38.08
F22b	2539		26.45	16.00	44.00	5.84	22%	50.83	39.72	68.65	40.80
C10	3611		28.64	18.50	46.50	5.55	19%	58.65	44.95	68.65	40.80
C11a	5353		29.03	18.75	48.75	5.79	20%	59.94	45.57	64.08	38.08
B15	9211		29.36	18.50	46.50	5.60	19%	61.11	46.72	68.65	40.80
F16	12,723		29.47	16.50	48.50	6.85	23%	61.01	45.00	60.07	35.70
E50	8555		29.87	16.00	44.00	5.34	18%	63.02	48.18	68.65	40.80
B61e	7738		30.63	16.25	46.25	6.01	20%	65.06	48.50	64.08	38.08
E64	6063		32.06	18.75	48.75	6.21	19%	69.13	49.55	64.08	38.08
C11b	216		32.24	20.75	46.75	6.32	20%	69.54	49.99	73.93	43.94
E27	11,043		32.60	18.75	48.75	6.51	20%	70.38	49.79	64.08	38.08
E51	11,348		32.63	18.50	46.50	5.75	18%	70.96	51.35	60.07	35.70
E53	2414		32.68	18.50	46.50	5.58	17%	71.18	51.88	68.65	40.80
B37	13,016		32.71	18.75	48.75	6.13	19%	70.91	50.31	64.08	38.08
B04b	5845		32.85	18.75	48.75	5.96	18%	71.38	50.64	64.08	38.08
E65a	1223		32.96	18.75	48.75	6.34	19%	71.41	49.95	64.08	38.08
E6b	5916		33.00	16.50	48.50	5.59	17%	72.00	51.85	60.07	35.70
D4	768		33.06	16.25	46.25	7.35	22%	70.98	47.11	64.08	38.08
E60a	944		33.16	20.75	46.75	5.70	17%	72.37	51.67	73.93	43.94
B4a	1720		33.17	18.75	48.75	6.16	19%	72.10	50.79	64.08	38.08
E71d	496		33.39	18.75	48.75	7.42	22%	71.69	47.38	64.08	38.08
E72a	3712		33.41	18.50	46.50	6.07	18%	72.71	51.10	68.65	40.80
B72a	1448		33.47	16.25	46.25	5.71	17%	73.12	52.36	64.08	38.08
E46a	1448		33.47	16.25	46.25	5.71	17%	73.12	52.36	64.08	38.08
B71b	1955		34.08	16.50	48.50	6.79	20%	73.80	49.39	64.08	38.08
E32b	2968		34.10	21.00	49.00	6.23	18%	74.21	50.83	68.65	40.80
JU5	6112		34.35	21.00	49.00	5.60	16%	75.22	52.36	68.65	40.80
E77	2161		34.46	21.00	49.00	6.68	19%	74.68	49.10	68.65	40.80
E71c	301		34.70	21.00	49.00	6.79	20%	75.09	48.34	68.65	40.80
B71a	2070		34.83	21.00	49.00	6.57	19%	75.55	49.23	68.65	40.80
E72c	257		34.97	20.75	46.75	7.32	21%	75.24	47.78	68.65	40.80
E72b	164		35.34	23.25	49.25	7.42	21%	75.88	44.27	73.93	43.94
E20	712		35.73	23.25	49.25	5.68	16%	77.98	51.54	73.93	43.94
Mean	4027		31.71	18.58	47.21	6.06	19%	67.07	47.28	67.56	40.15
SD	3812		3.64	2.16	2.21	0.77	2%	11.57	6.72	5.59	3.32

Results

Machine OBC derived tree data

Descriptive statistics as well as the weighted mean and marginal productivity for each of the 35 machine OBC derived stands are detailed in Table 3. The table further shows the mean DBH 31.7 cm and SD 6.6 cm (CV of 19%). The DBH range between the 10th and 90th percentile remained constant with the bulk of the tree data between 18.75 and 47 cm. The SD for all the means of the stands is also shown in the table.

The mean productivity for the stand data was tested statistically (t-test) and showed that the weighted mean and marginal productivities for the Bears were similar (67.07 vs. 67.55 $m^3 \cdot PMH^{-1}$) while in the case of the Beaver the weighted mean productivity (47.27 $m^3 \cdot PMH^{-1}$) was significantly higher than the marginal productivity (40.14 $m^3 \cdot PMH^{-1}$).

Generated tree distribution data

For these data, in the case of group one (DBH 25 cm) the weighted mean productivity figures increased as the CV increased for both machine types (Table 2). For group two (DBH 30 cm), weighted mean productivity remained largely constant for three levels of CV, while for group 3 (DBH 35 cm), productivity decreased with increasing CV, especially so for the smaller size Beaver machine. For the normal distributions using the same mean and CV, the weighted mean productivity decreases as the CV increases for all cases.

Differences between weighted mean productivity derived from the Weibull distribution and the Normal distribution are considerable for the Beaver in the smaller tree size (mean DBH 25 cm) where a productivity estimate based on an assumption of normality is 8.02 $m^3 \cdot PMH^{-1}$ higher for a CV of 15, 6.7 $m^3 \cdot PMH^{-1}$ for a CV of 20, then 3.05

$m^3 \cdot PMH^{-1}$ lower when CV increases to 25 (Table 2 /Fig. 2). In the largest tree size class (mean DBH 35 cm), the difference is 4.58 $m^3 \cdot PMH^{-1}$ for a CV of 20 and 4.12 $m^3 \cdot PMH^{-1}$ for a CV of 25.

The plotted set of nine generated distributions appear in Fig. 3.

Increasing the CV (each row in Fig. 3) shifts the tree size distributions to the right, irrespective of initial mean diameter. As a result, more of the larger trees are harvested and mean weighted productivity lines are extended. For the largest mean diameter class (35 cm) the mean weighted productivity for the smaller Beaver begins to decline with an increasing CV as the marginal productivity function is sensitive to oversize trees.

As the CV increases so does the maximum of the weighted mean productivity (determined through the 1st derivative for the curve) for each of the mean DBH in the generated scenarios. In all cases, as the CV increases for a particular mean DBH, the peak (maximum) mean productivity occurs later in the DBH range. As the mean DBH increases so does the marginal productivity for each machine type.

For the smaller Beaver, weighted mean productivity increases fastest for the distributions with the lowest CV, irrespective of tree size (Fig. 3). For the distributions with the largest mean diameter (35 cm), this difference is maintained, while for the smallest (25 cm), the distribution with the largest CV (25%) ultimately results in a higher weighted mean productivity. The lower the CV, the earlier the curve terminates on the x-axis, meaning that fewer larger trees exist in that distribution. This difference is more pronounced for the stands with smaller mean DBH. The effect of this on productivity differs between curve families and between machine sizes.

Separate weighted mean productivity curves for the Beaver (Fig. 4) and the Bear (Fig. 5) were plotted.

In the case of the Beaver (Fig. 4), the weighted mean productivity curves peak at roughly the same point for the smaller DBH group. As the trees mean DBH increases

Table 3 Weibull parameters and weighted mean productivity results for each of the generated distributions scenario groups (Weibull and Normal distribution)

Distribution scenarios				Weibull distribution			Normal distribution		
				Distribution parameters		Weighted mean productivity ($m^3 \cdot PMH^{-1}$)	Weighted mean productivity ($m^3 \cdot PMH^{-1}$)		
Group	DBH (cm)	SD (cm)	CV %	α	β	Bear	Beaver	Bear	Beaver
1	25	3.75	15	7.923	26.558	45.57	28.39	45.82	36.41
		5	20	5.794	27.000	46.09	28.62	45.74	35.30
		6.25	25	4.542	27.380	46.97	29.09	45.61	26.04
2	30	4.5	15	7.923	31.870	63.87	42.94	64.23	43.51
		6	20	5.794	32.400	63.48	42.15	63.85	42.86
		7.5	25	4.542	32.856	63.33	41.21	63.49	41.70
3	35	5.25	15	7.923	37.182	76.95	52.69	77.81	54.22
		7	20	5.794	37.800	75.79	49.77	77.12	54.35
		8.75	25	4.542	38.332	74.45	46.22	76.26	50.34

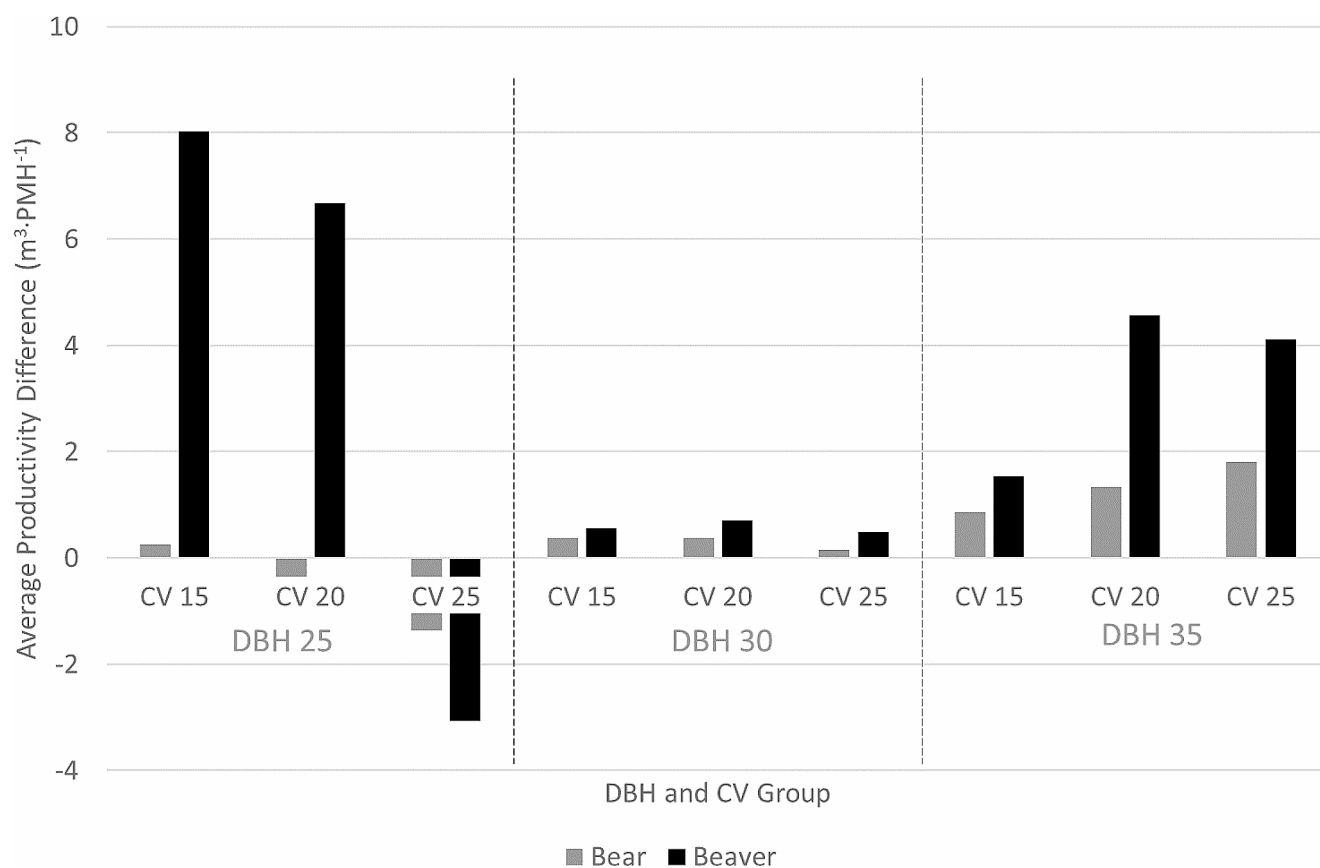


Fig. 2 The difference between weighted mean productivities based on assumptions of Normal and Weibull distributions for each DBH and SD group

greater than 25 cm there is greater variation in the weighted mean productivity peak. The comparison of weighted mean productivity indicate the smaller sized Beaver is much more sensitive to larger tree sizes.

In the case of the larger Bear machine (Fig. 5), there is almost no variation in the maximum weighted mean productivity for all the DBH and CV groups, although there is a little in the larger DBH group for this machine. There is an interesting trend for each of these curves, there are differences between the machine productivity at the mean DBH vs. the weighted mean productivity across the full tree diameter distribution. For example, the curves show a machine productivity for a mean DBH of 35 cm (the largest DBH grouping) of $68.4 \text{ m}^3 \cdot \text{PMH}^{-1}$, $63.63 \text{ m}^3 \cdot \text{PMH}^{-1}$, and $59.23 \text{ m}^3 \cdot \text{PMH}^{-1}$ for the 15%, 20% and 25% CV respectively for the Bear. This indicates a discrepancy when modelling machine productivity on the mean tree vs. across the distribution of trees. The same trend is true for the Beaver.

Discussion

Stand tree size distributions

Machine derived OBC data yielded 35 individual stands for the four machines. In clearfelling operations, it is normal practice for the company to have the two larger or the two smaller harvesters working in pairs in the same stand as the harvesting component of the system. The mean tree number for all the sites was 4026 (minimum of 164 tree and maximum of 13,016), this variation is due to partial completion of stands (not the full area being harvested before these data were downloaded and processed) and to a lesser extent to basic data cleaning as per the method detailed in Ackerman et al. (2022). The DBH distribution of the data did remain somewhat consistent between the 10th and the 90th percentile. The mean DBHs for these sites are consistent with mature stands for pine saw timber regimes in South Africa (Kotze et al. 2012). The distributions of these stands were found to have a mean DBH of 31.7 cm and SD of 3.6 cm (coefficient of variation of 11%). The lack of larger variation between stands in the study could be considered a

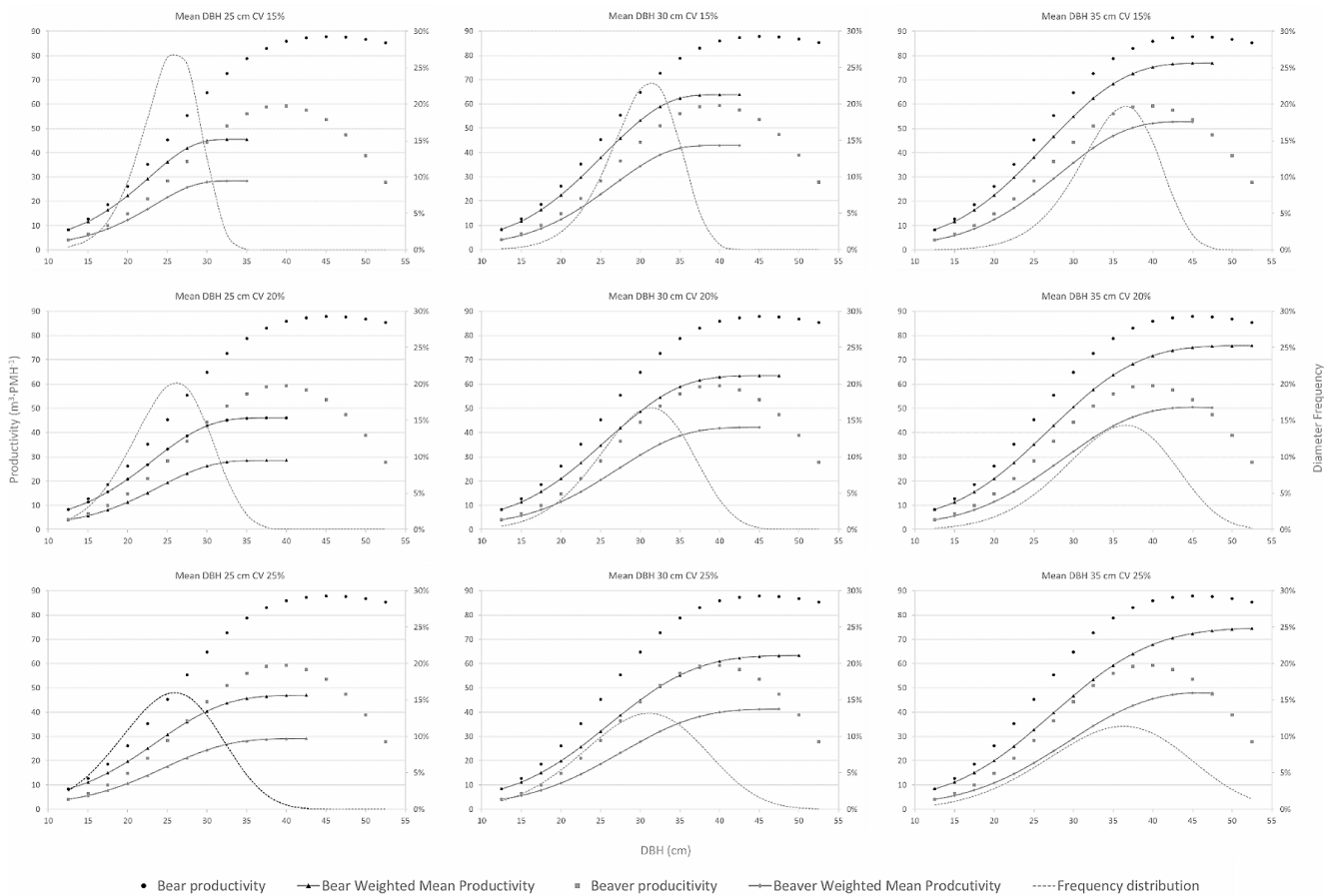


Fig. 3 Graphical results based on the generated distributions, for each case the distribution of the marginal (dots) and mean weighted productivities (solid line) for each machine are plotted. The dotted line

drawback, but also the motivation for generating a generic set of Weibull distributions.

Marginal vs. mean productivity

The study analysed and processed machine derived harvesting data to acquire information regarding close-to-real tree distribution information. Although these data were acquired from a follow-up study, the standard of the data is thought to be acceptable and close to real, due to the machines being calibrated regularly (Strandgard and Walsh 2011; Strandgard et al. 2013; Alam et al. 2014; Brewer et al. 2018; Kemmerer and Labelle 2021) and in practice in the operation.

Mean productivities are split into the marginal and the integrated or weighted mean values. In the case of the Bear machine, these values are similar while they differ in the case of the Beaver for this data set. The integrated mean values were derived from the productivity model presented by Ackerman et al. (2022), but on the range of DBH’s for each stand. Compared to the previous study (Ackerman et al. 2022) the mean of the mean productivities is higher, due

shows the tree size distribution. Each column represents a diameter class while each row represents increasing CV.

to the mean DBH’s being higher. However, in the case of the Beaver, the integrated mean being lower indicates the distribution of these stands tending toward the larger DBH where the Beaver becomes less productive to operate.

Productivity in relation to machine derived tree-size distributions

Running the given productivity functions on the 35 actual stand distributions as against on the uniform distribution made no perceivable difference to the productivity rate for the larger Ponsse Bear (67.1 vs. 67.6 $m^3 \cdot PMH^{-1}$), although the SD halved from 11.6 to 5.6 in the case of the uniform tree distribution. This suggests that the larger machine has enough processing capacity to retain a high productivity rate over a larger range of tree sizes, i.e., it is less sensitive to tree size. It also suggests that the more uniform the tree size distribution, the more predictable that productivity rate will be. However, for the smaller harvester (Ponsse Beaver), productivity decreased by 15% from 47.3 to 40.1 $m^3 \cdot PMH^{-1}$ while the coefficient of variation (CV) dropped

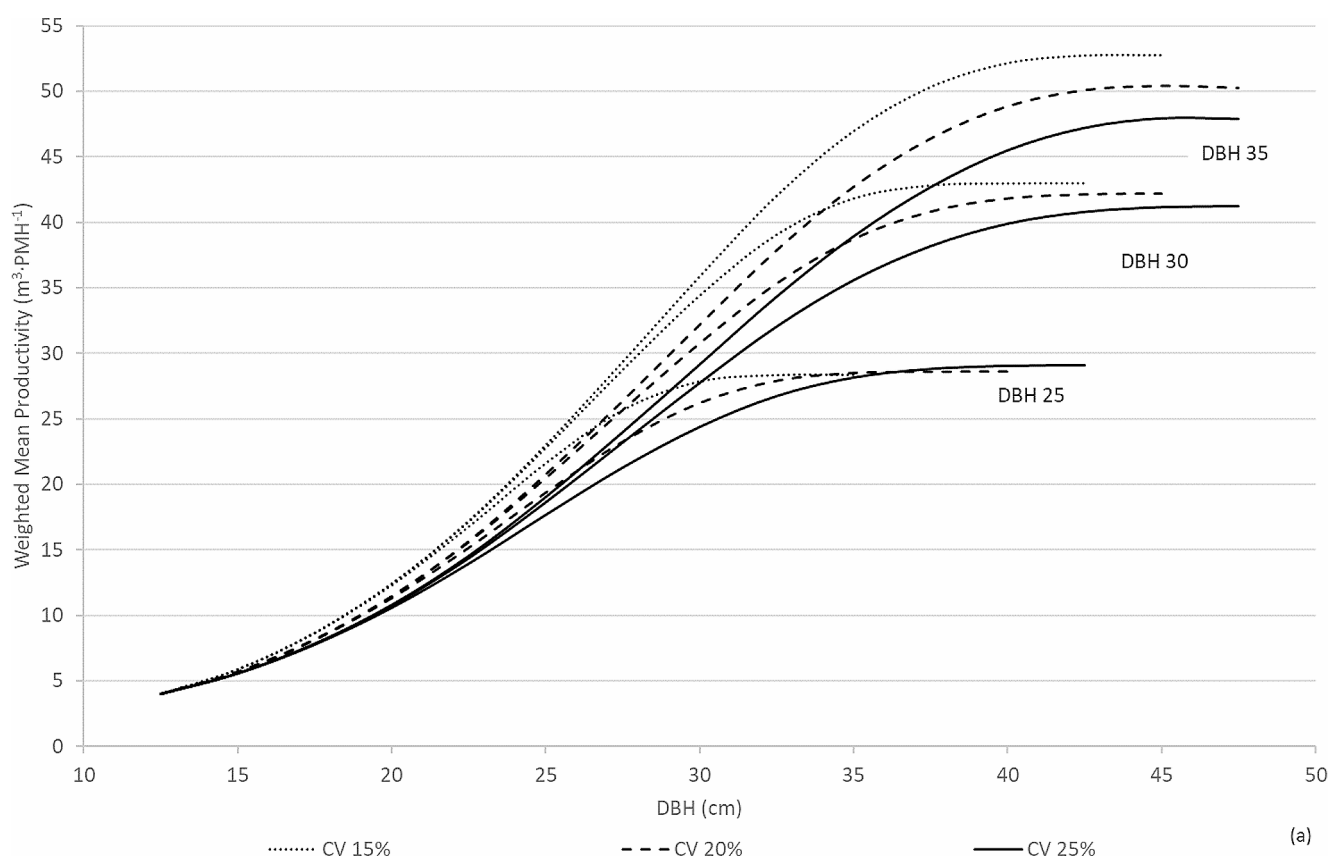


Fig. 4 Weighted mean productivity curves for the smaller capacity Beaver, for each of the mean DBH's and CV of the mean DBH.

by 6% in the same transition to a uniform distribution. This indicates that the production capacity of the smaller machine is more sensitive to variation in tree size, which could also be expected since the machine has less mechanical capacity for, in particular, the larger trees in stands of high variation. The comparison clearly shows that different distribution shapes have different effects on different machine sizes, therefore one should be cautious in assuming trends being applicable for harvesters in general. The absolute differences in productivity between the machine size classes (67 vs. 47.3 and 40.1 $\text{m}^3 \cdot \text{PMH}^{-1}$), while not of direct relevance to the study, reflect the fact that only final felling stands are included in the study where the smaller Beaver is generally operating at or beyond its design specifications.

The productivities were higher than those presented in other studies on long term data (Wenhold et al. 2020) and in observational time studies presented by Williams and Ackerman (2016). Similarly, these productivities are also higher than the theoretically modelled productivities in Ackerman et al. (2022).

In general, it is unlikely that tree size distributions will be uniform, as tending and silvicultural practices in plantation forestry (thinning from below) would result in a left skewed distribution, while thinning from above and below, which is commonly employed in e.g. European stands (Rouvinen

and Kuuluvainen 2005), would lead to a bimodal distribution of the trees removed, and a normal approximation of the residual stems.

Productivity in relation to generated tree size distributions

To further illustrate the effect of different underlying distributions on the two harvester sizes studied, a family of Weibull distributions was generated. In our case, three mean DBH classes (25 cm, 30 cm, and 35 cm) and three levels of CV (15%, 20%, 25%) for each DBH class were used, and the parameters for Weibull functions describing each were estimated using MS-Solver. The DBH and CV classes were derived from the data from the 35 original stands. The generated stand Weibull parameter α (shape parameter) remained the same for all the distributions, while the β (scale parameter) varied for each, which was expected. For each of the iterations, increasing the CV resulted in a flattening of the distribution within each DBH class. However, for each of the resultant tree size distribution curves (Figs. 3, 4 and 5) the significant differences in productivity between machine types and between DBH classes within machine types, conformed to expectations (Table 2).

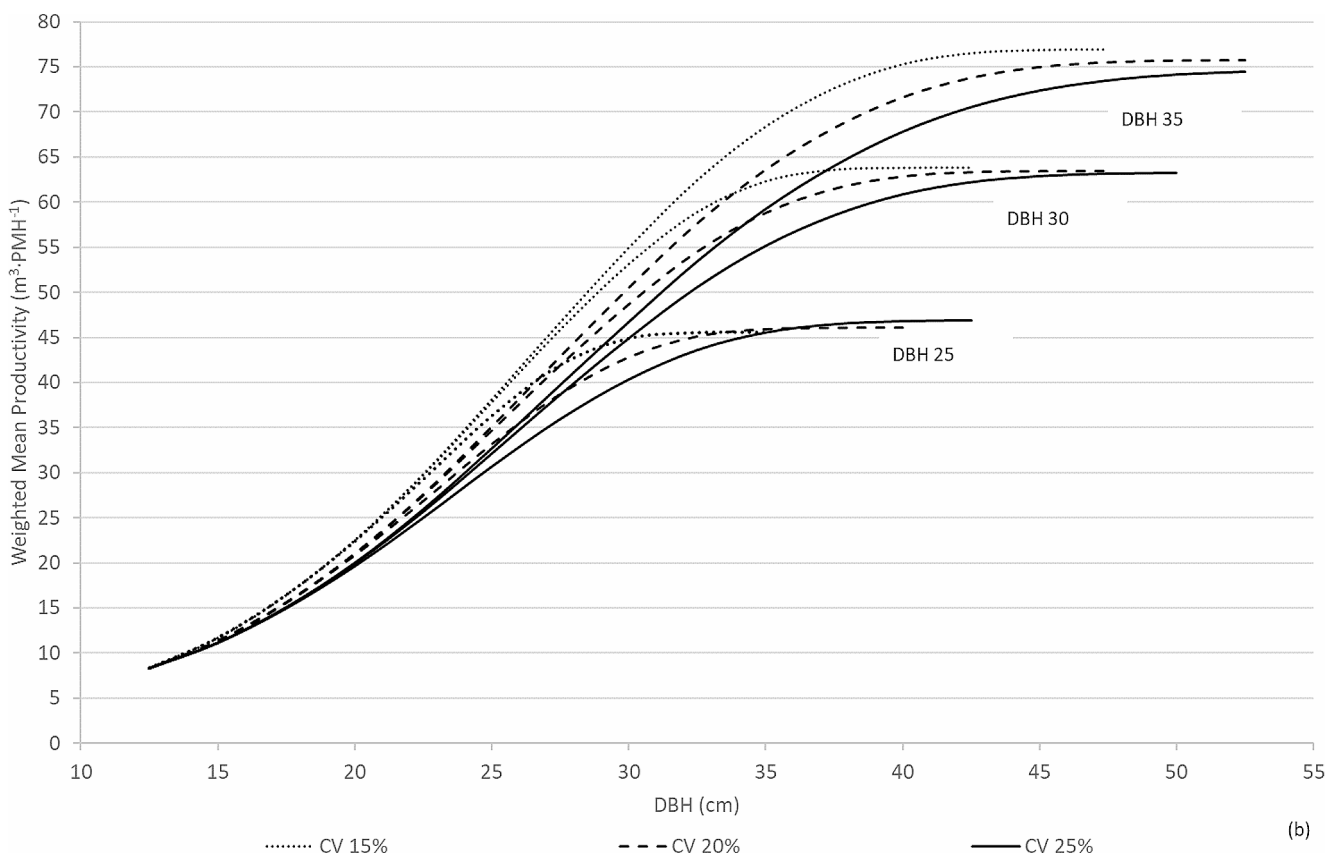


Fig. 5 Weighted mean productivity curves for the larger capacity Bear, for each of the mean DBH's and CV % of the mean DBH.

However, the productivity curve and the implications this might have on harvester performance was of greater interest. For both machines, CV played an important role throughout the DBH range, where productivity increased far more rapidly and terminated earlier for the lowest CV (15%) than for the CV (20%) and CV (25%). For the smaller Ponsse Beaver working in the biggest trees (mean DBH 35 cm), the machine productivity on the CV (15%) curve was substantially higher than for the CV (20%) and CV (25%) curves throughout. The curve truncates earlier as the right tail of the tree size distribution terminates at a smaller DBH than for the higher CVs. In the smallest trees (mean DBH 25 cm), the productivity curve with the highest CV (25%) marginally exceeded the others as the bigger trees generated the higher variation, ultimately increasing the weighted mean productivity. Pettersson (2017) corroborates this outcome in his study, stating that a larger diameter distribution (larger CV) reduces harvester productivity by 5–9% compared to a stand with a narrower distribution (lower CV) given the same mean DBH. Our study showed very similar results in the large and medium tree sizes, however for the smaller trees (mean DBH 25 cm) the differences were negligible (Table 2). Whereas Pettersson (2017) used mean tree volume and CV in a multiple regression where each data point

represents a stand, in the current study we run the productivity function across the tree size distribution of each stand.

A noteworthy outcome of this comparison being that within a given machine size class, there is an interaction between mean DBH and CV that provides relative and absolute differences that are unique for each combination. The effect of this might be more significant in a thinning than in a clearfelling situation, although this was not tested in the study. Assuming a thinning-from-below situation in Figs. 4 and 5, for a given mid-range DBH on the x-axis (the target diameter for thinning), weighted mean productivity differences of up to 20% can exist between the lowest performing (high CV) and the highest performing (low CV) productivity curves. Considering that thinnings are often economically marginal, knowing which curve one is working off could be of importance for correct price setting and overall economic feasibility. However, no thinning operations were included in the study so these trends are speculative. Pettersson (2017) did not find any relationship between productivity and CV in thinning operations, but the practice of thinning from above and below in Nordic forestry might have nullified this.

Overall, there was an expectation that the productivity differences found because of differing CVs would be larger in the present study than the 5–9% found by Pettersson (2017).

This was assumed as that study used a linear approach to model productivity, which assumes a constant rate of increase across a diameter range. Also, a regression model estimates only the marginal or instantaneous level of productivity, whereas the volume weighted productivity rates used in this study, take the tree size distribution into account, even if it is an extreme representation, e.g., bimodal. Finally, mean tree sizes in the study by Pettersson (2017) were considerably smaller (0.26 m³ at clearfelling and 0.09 m³ at thinning), than those in the present study (> 0.75 m³ at clearfelling) and given the abrupt ranking changes with marginally decreasing DBH classes in Figs. 4 and 5, it is not possible to make direct comparisons operations using considerably smaller trees.

The relationship of the standard deviation to mean DBH, or CV has been shown to play an important role in predicting productivity under the given conditions in this study. The field data shows that CV does not increase linearly with increasing mean stand DBH but tapers off (Fig. 1). To represent a wider range, we selected the three classes (15%, 20% and 25%) to cover the range of observations across the dataset, more than the mean CV of each DBH group (Table 3). In most industrial plantation forestry across the world, trees grown on a saw-timber regime would typically receive one to three thinnings during a rotation, with the express intention of lowering the CV. By contrast, in a boreal stand, Pettersson (2017) showed CV values of 34.6–37.2% in final felling. The CV, or other indices describing the relationship of the mean and SD, is seldom used in productivity studies on single stands, but could be important to include in large follow-up studies. Ottaviani Aalmo et al. (2021) applied both the mean tree size and SD in a multiple regression in an efficiency study in a boreal setting constituting semi-natural forests to little effect. However, this might have been since they were unlinked, potentially nullifying each other. A high CV typically correlates with low forest management intensity and represents a shift in responsibility (cost) from the forest manager to the contractor.

In this study, productivity differences of up to 8 m³·PMH⁻¹ were found in the most extreme cases. A prior knowledge of the tree diameter distribution would be useful in the planning phase, allowing for a more accurate scheduling of operations. Such data could be collected through manual enumeration or through remote sensing where diameter distributions have been shown to be attainable with low associated error (Maltamo et al. 2019).

Conclusions

Within the 35 harvested stands tested in this study, productivity on the large harvester (Ponsse Bear) was unaffected within the given ranges of tree sizes and CV but was more predictable in a uniform tree distribution (SD was halved).

For the smaller harvester (Ponsse Beaver) productivity decreased by 15%, and SD by 50%, when moving from the natural stand distribution to a uniform distribution.

For the more generic Weibull generated distributions, which described a wider range of mean diameters and CVs than the collected harvester data, the following conclusions were reached; (i) For both harvester sizes in the smaller mean DBH class, net overall productivity was highest in the stands with the highest CV, while this was reversed in the stands with larger mean DBH, here productivity was highest in stands with the lowest CV, (ii) Differences in productivity for each combination of mean DBH and CV used were more pronounced for the smaller harvester than for the larger harvester, (iii) An assumption that of one of the Weibull generated stands being normally distributed would result in a mean productivity difference of up to 8 m³·PMH⁻¹ on the small machine in smaller trees and around 4 m³·PMH⁻¹ in larger trees. Finally, there is a difference in the way that harvesters of different size classes will respond to changes in tree distributions, and this should be kept in mind when scheduling harvesting operations with machines with different design capacities.

Author contributions SA and BT contributed to the concept, analysis and writing of the document, JB contributed to aspects of the simulation modelling for the distributions presented in the document. SA, BT, RA and JB contributed to the overall proofing, formatting and presentation of the document.

Funding Open access funding provided by Stellenbosch University. This project was partly funded by the South African Department of Science and Technology – Forestry Sector Innovation Fund. This fund was administered by Forestry South Africa.

Open access funding provided by Stellenbosch University.

Data availability No datasets were generated or analysed during the current study.

Declarations

Conflicts of interest The authors declare that they have no conflict of interest.

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