

# The Human Influence on Productivity in Harvester Operations

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## Abstract

It is well-known that machine operators vary in their performance when undertaking mechanized forestry harvesting operations. Nevertheless, the human factor is still largely disregarded in productivity calculations. In the present study, operator performance is evaluated by analysing archived production data collected automatically by computers on-board single grip harvesters driven by 32 operators working in 3,351 stands over a period of three years. The experimental conditions were all approximately the same. The effect of the operators is modelled by a multilinear regression analysis. Seventeen operators were found to have performance levels that differed significantly from the mean model. Together, 'tree volume' and 'operator' explained 84% of the overall variance. However, since 37.3% of the variance in productivity is explained by the operator, the influence of the operator on productivity is quite large. The minimum and maximum significant mean productivity values for all the operators differed by a factor of 2.2, which reduced to a factor of 1.8 if only data from experienced operators were analysed, although this still demonstrates that the best operators are nearly twice as productive as the worst. The operator, therefore, has an important influence on productivity and should be considered a key factor in productivity models.

*Keywords:* Germany, harvesters, logging documents, operations, *Pinus sylvestris*, productivity, thinning.

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## Introduction

Single grip harvesters are used in many regions of the world to gather a large proportion of the total timber harvest. They can achieve high productivity levels but are expensive pieces of machinery and therefore have to work very efficiently. Many factors influence their productivity. Most of these have previously been analysed and described in the literature (Purfürst 2009); however, one variable is often disregarded when considering mechanical work performance: the human factor.

The variability in the performance of operators can be high, not only among different operators but also for an individual over time. Consequently any calculations or planning that does not account for such variation in operator performance may introduce errors, which, to date, have not been fully quantified. Indeed, the influence of the harvester operator on the productivity of the whole harvesting system has long been disregarded (Purfürst 2009, Purfürst and Erler 2006, 2007), although "*A skilled operator is essential if the investment in the machinery is to be maximized by the contractor.*" (Kirk et al. 1997).

The productivity of machine work depends much more on the abilities of the human operator than does motor-manual work (Andersson 1988). Research quantifying the influence of harvester operators generally includes data from only a small number of operators. Such analyses indicate the influence of the operator to be around 20–50% (Glöde 1999)

or 40–55% (Anonymous 2003). Large productivity differences of up to 40% have also been observed for different operators using the same harvester (Kärhä et al. 2004, Ovasikainen 2005).

The performance levels of operators do not remain constant over time either. Fluctuating performance levels within a single day and on different days are usual (Purfürst 2009). The learning curves of operators who are mastering use of the harvester are also influential and can change the achievable performance level of operators by as much as a factor of two (Purfürst 2010).

Differences in the productivities of operators are significantly higher when conducting first compared to second thinnings (Kärhä et al. 2004), and the larger the tree diameters the greater the differences between machine operators (Anonymous 2003). Thus, the differences increase as the

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work situation becomes more difficult (e.g., increasing slope, stand density, curved trees, branches on the skid road), and the more it differs from a normal situation (Väättäinen et al. 2004b). However, higher operator productivity does not necessarily correlate with lower work quality, e.g., damage to any remaining trees (Purfürst 2010).

Quantifying the influence of the harvester operator in isolation from other influential factors is difficult since it is challenging to construct a formal experimental control (Kärhä et al. 2004, Neruda and Valenta 2003). Moreover, a direct evaluation of performance is only possible for work sequences in which the operator has a direct impact (Backhaus and Stolzenburg 1988): operators primarily have an influence during the production process; their influence is negligible when simply moving material (Nimz 2002).

Many of the differences between operators are due to the number of decisions that need to be made quickly and continuously during the handling of machinery (Korhonen et al. 2004). Thus, a key aspect of high performance is an operator's tacit knowledge (Harstela 2004, Parise 2004). An excellent harvester operator handles more working elements simultaneously than a less efficient operator, moves the boom along a shorter path (Harstela 2004, Jacke and Wagner 2001, 2002), keeps the boom moving nearly all the time (Väättäinen et al. 2004b), achieves a better and more efficient boom working angle (Väättäinen et al. 2004b), and is able to position the grip of the harvester head exactly and optimize saw cuts (Brunberg et al. 1989). A good operator has fine motor skills, is always planning four to five stems in advance (Peltola 2004, Ranta 2004), and exhibits little variation in their processing time for different stems (Ovasikainen 2005). Thus 10–15% of the differences in the performance of harvester drivers are due to differences in technique, 20–30% are due to a more efficient crane and generator control, and 50–55% are the result of better planning and decision making (Väättäinen et al. 2004a).

Because of these uncertainties and in order to avoid systematic errors in calculating the productivity of machinery work, it is essential to evaluate the influence of the harvester operator. However, productivity models of forest machinery have often disregarded the human factor, despite the fact that it is an important yet clearly unquantified factor influencing productivity. The objectives of the present study are, therefore, to determine the extent of these differences and to quantify the impact of variation in human factors on the performance of forest harvesting operations involving cut-to-length systems.

## Materials and Methods

### Environmental Conditions

The study sites were located in Germany: mainly in East Germany and in Bavaria, South Germany. The study analyses historical production data that were collected by on-board computers in single grip harvesters over a period of three years. The research is based on the analysis of data from several similar stands and similar harvesting systems.

For the purpose of comparison, the historical production data were evaluated and selected according to the following criteria:

- Due to the study region and the desire to examine a large quantity of data with relatively few influencing factors, only Scots pine-dominated stands were selected. Spruce, larch and hardwood-dominated stands were not included. Therefore, over 90% of the harvested trees were pines (*Pinus sylvestris* L.). The percentages of other tree species included in the data were: 6.1% Norway Spruce (*Picea abies* (L.) H. Karst.); 0.6% Larch (*Larix decidua* Mill.); 1.7% Birch (*Betula pendula* Roth); and 0.7% hardwoods.
- Due to the nature of the study region, only sites with slope of less than 10% were included.
- Three different types of similar-sized harvesters used in first or second thinnings were selected (John Deere 1070, Valmet 901, and Ponsse Beaver).
- Data for which there was incomplete information about the stand or the operator were not used.

After the filtering process, data from a total of 3,351 of the original 7,584 stands were selected for inclusion in the analysis. The harvesting system in all operations includes only a first or second thinning of pre-market trees from young stands using a cut-to-length (CTL) system employing a single-grip harvester. In most stands, working lines (skid roads) with an average distance of about 20–24 m between them were only created during the first thinning. The work may have been performed at any time throughout the whole year during daylight or night hours.

### Operators

The performances of several operators are analysed and evaluated. From the available information relating to 52 operators, only 32 were included in the analysis after selecting the data according to the above criteria and due to a requirement that there should be data from at least 15 stands (working areas) for each operator.

Because the sampling of operators was not detailed planned, there were differences in the operators' educational and practical backgrounds. Some of the operators had learned their skills in a harvester education programme or on a course at a forestry academy. These courses varied from one day to seven weeks. More than half of the operators (59%) had completed an additional three years training as a forest technician. Some (22%) had completed education in a different field such as mechanics, carpentry or butchery, and had learnt harvesting on-the-job. Their ages ranged from 18 to 48 years (median 25).

Their previous experience working on the harvester undertaking thinning also varied, ranging from beginners (38%) to experienced (62%) operators who had been working in this field for up to seven years. In accordance with previously published studies, an operator in the present study is defined as "experienced" if he has at least one year of relevant work experience on a CTL harvester (Calabrese 2000, Jacke and Wagner 2002, Purfürst and Erler 2006, Purfürst 2010).

## Historical Production Data

The study is based on logging operation data collected from the harvesters' on-board computers. Output data were collected as part of the normal work process through the automatic data recording systems of harvesters. Information about the production and operator are stored in various standard files using the StanForD-Standard (Skogforsk 2007). These files are used to record the total harvesting production data (\*.prd), harvesting production data for each individual log and stem (\*.pri), operational monitoring data (covering both work time and repair time data, \*.drf), and stem data (length and diameter values, \*.stm).

A program written by the author is able to analyse the huge number of StanForD files, by extracting the different variables from every file. A major issue is that the StanForD-Standard has many different versions: there is variation in the types of software used to collect the data, and there are various versions installed in the harvesters. It is, therefore, very difficult to analyse the data automatically because different versions of the StanForD-Standard are implemented. Despite these difficulties, the data were written into a database. The G15-time, which is defined as the number of hours of effective machine time, including downtime not exceeding 15 minutes per occasion, was used for most of the analyses. The G15-time is comparable to the Productive Machine Hour (PMh15). Additional information on stand, times, dates, harvesting data, name of operators and software is also included. For example, the following are recorded: Effective time, Move time, Run time, Work time and Repair time.

In the final analysis, 4.5 million stems from 3,351 stands were analysed; this represents approximately 0.65 million m<sup>3</sup> of harvested wood, with a mean volume of 0.147 m<sup>3</sup>/tree, and an arithmetic mean production of 9.8 m<sup>3</sup>/PMH15 (geometric mean: 8.93 m<sup>3</sup>/PMH15). Data about logging were collected during the period December 2003 to September 2006.

## Data Analysis

The analysis is based on data from every stand. Because the size and duration of the operation in each stand differed, the information had to be standardized, based on the time variable. These data were analysed using standard statistical programs (e.g. SPSS17).

The information about stems, times, and harvested volume was used to create performance information for every stand and operator. In order to compare operators it was necessary to identify a reference performance level. The choice of the model is difficult and needs to be based on the available data and the objective (Purfürst 2009). Due to the large influence of tree volume on harvesting productivity, and the simple and comparable environmental conditions, the only influential factor included in the comparison of operator productivity was tree volume. Thus, in the present study, a logarithmic regression model based on tree volume was used as to represent the whole population.

The basic correlation can be expressed as a logarithmic curve:

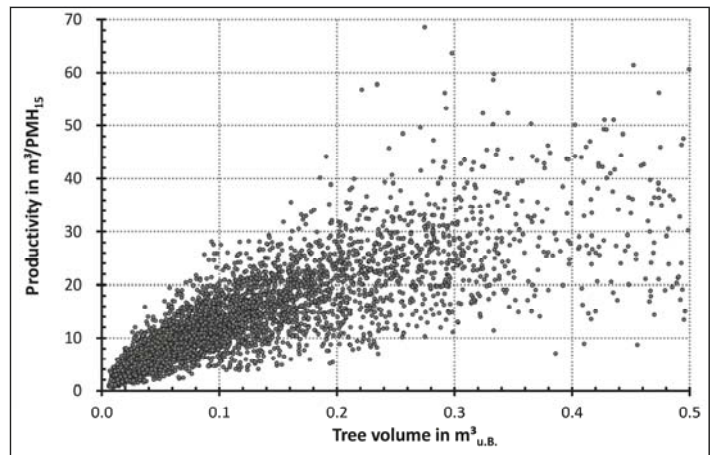
$$P = b_0 + b_1 \ln( tvol ) \quad [1]$$

where P describes the productivity in m<sup>3</sup>/PMH15 and b<sub>0</sub>, b<sub>1</sub> are the two parameters of the linear regression equation. The independent variable (tvol) is tree volume under bark calculated using regional bark-functions (Purfürst 2009).

It has been shown that the measured time and performance did not to follow a standard distribution but were log-distributed (Purfürst 2009), as found by other researchers (Erler 1994, Reichel 1997). The data used in the present study even indicate that the assumptions underlying the calculation of a standard deviation for this data are wrong.

Furthermore, when calculating a linear regression, the data must be homoscedastic, i.e. with a constant variance that is independent of the size of the influential factor. Figure 1 shows the measured productivity as a function of tree volume for the data in the current study. This shows the typical 'cornucopia' shape for the measured data, indicating heteroscedasticity. Hence, the use of a linear regression is, strictly speaking, not permissible. If the error terms of the data do not have the same variance, the least squares method cannot be legitimately used to estimate the regression coefficients.

**Figure 1:** Productivity data plotted against tree volume

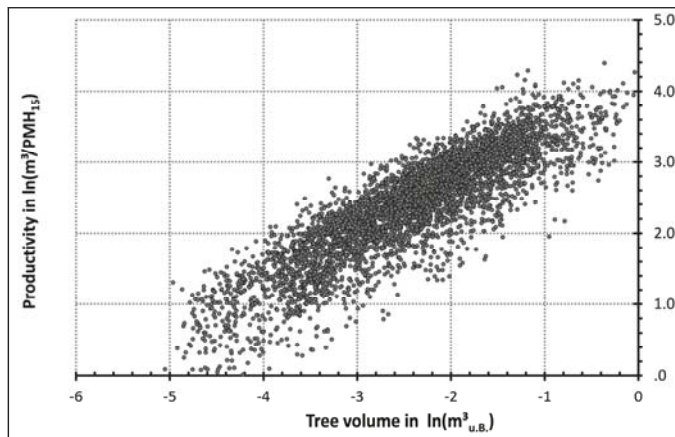


In order to solve these statistical problems it is necessary to apply a logarithmic transformation to the dependent variable (time or performance).

$$\ln( P ) = b_0 + b_1 \ln( tvol ) \quad [2]$$

Figure 2 shows the results when both tree volume and performance have been transformed to logarithms. It is apparent that the data are nearly homoscedastic and a linear model will fit the regression well. Hence, the prerequisites for the linear regression are met.

**Figure 2.** Logarithmically transformed productivity data plotted against logarithmically transformed tree volume.



Empirical data were almost exclusively used for the statistical analysis. Generalization of inferences based on such data is possible when they relate to the independent variable between the 5% percentile and the 95% percentile (Fricke 2004, Sachs 2004). In the current study, therefore, statements are only based on data pertaining to the tree volume interval between 0.04 m<sup>3</sup> and 0.32 m<sup>3</sup>.

## Results

The differences in productivity between the stands were large. It should, therefore, be possible to discover some of the underlying causes of these differences by analysing the influence of tree diameter, machine, and operator.

### Effect of Machine Type on Harvesting Productivity

Three different types of harvester were used during this study. A regression analysis based on dummy variables revealed no significant differences between the three types of harvester ( $p_1 = 0.84$ ,  $p_2 = 0.45$ ) and they are therefore considered comparable. In a covariance analysis, only 0.09% of the variance can be explained by the type of harvester and only 0.11% of the variance by the interaction between type of harvester and tree-volume. Therefore, the influence of the harvester type is not considered further in this study.

### Variation in Performance Among Different Operators

The data analyses based on long-term logging data indicate that there are differences in the performance of different operators. To determine the statistical significance of these differences a multilinear regression analysis using dummy variables was performed (Draper and Smith 1981, Heinimann 1998).

Due to the log-normal distribution of human performance (Purfürst 2009, Erler 1994), the model uses logarithmically transformed performance as the dependent variable (ordinate). In addition, to produce a linear function, the model uses the logarithmically transformed tree-volume (logarithmic model) as the independent variable (abscissa). To describe the effect of the operators, 32 dummy variables

were added into the regression analysis. Thus, 66 parameters had to be estimated.

Table 1 shows the results of the (dummy) regression analyses. The parameter estimates give an indication of the differences between the operators. An analysis of the residuals shows that the regression data have a nearly normal distribution.

**Table 1.** Harvester ground data summary

Parameter	estimate	SE	SE Coeff	t <sub>score</sub>	Sig.
(absolute term)	3.543	0.041	87.154		0.000
ln(tv <sub>ol</sub> )	0.631	0.019	0.736	32.906	0.000
Operator No. 14	-0.663	0.066	-0.398	-10.008	0.000
Operator No. 24	-0.916	0.098	-0.428	-9.337	0.000
Operator No. 2	-0.724	0.089	-0.401	-8.107	0.000
Operator No. 21	-0.977	0.125	-0.216	-7.803	0.000
ln(tv <sub>ol</sub> )*Operator No. 24	-0.294	0.045	-0.300	-6.497	0.000
Operator No. 9	-0.639	0.104	-0.236	-6.123	0.000
Operator No. 11	-0.796	0.152	-0.271	-5.242	0.000
Operator No. 5	-0.712	0.147	-0.153	-4.855	0.000
ln(tv <sub>ol</sub> )*Operator No. 14	-0.156	0.033	-0.185	-4.763	0.000
Operator No. 23	0.212	0.254	-0.142	-4.640	0.000
ln(tv <sub>ol</sub> )*Operator No. 23	0.090	0.054	-0.125	-4.685	0.000
Operator No. 8	-0.363	0.079	-0.153	-4.566	0.000
ln(tv <sub>ol</sub> )*Operator No. 21	-0.275	0.061	-0.124	-4.478	0.000
ln(tv <sub>ol</sub> )*Operator No. 2	-0.169	0.038	-0.226	-4.430	0.000
ln(tv <sub>ol</sub> )*Operator No. 8	-0.166	0.038	-0.147	-4.414	0.000
Operator No. 13	-0.309	0.072	-0.141	-4.304	0.000
ln(tv <sub>ol</sub> )*Operator No. 16	0.113	0.028	0.156	4.089	0.000
Operator No. 28	-0.681	0.175	-0.203	-3.895	0.000
ln(tv <sub>ol</sub> )*Operator No. 11	-0.241	0.063	-0.201	-3.841	0.000
ln(tv <sub>ol</sub> )*Operator No. 9	-0.156	0.049	-0.123	-3.175	0.002
Operator No. 16	0.182	0.058	0.122	3.160	0.002
ln(tv <sub>ol</sub> )*Operator No. 1	0.164	0.053	0.148	3.091	0.002
ln(tv <sub>ol</sub> )*Operator No. 18	0.176	0.061	0.072	2.907	0.004
ln(tv <sub>ol</sub> )*Operator No. 15	0.086	0.030	0.101	2.820	0.005
Operator No. 15	0.179	0.064	0.100	2.781	0.005
ln(tv <sub>ol</sub> )*Operator No. 12	0.145	0.060	0.108	2.429	0.015
Operator No. 7	0.113	0.057	0.081	1.975	0.048
Operator No. 10	-0.737	0.384	-0.102	-1.919	0.055
Operator No. 25	-0.987	0.546	-0.070	-1.808	0.071
ln(tv <sub>ol</sub> )*Operator No. 5	-0.112	0.064	-0.056	-1.766	0.078
ln(tv <sub>ol</sub> )*Operator No. 7	0.043	0.028	0.061	1.532	0.126
Operator No. 23	0.123	0.081	0.069	1.514	0.130
Operator No. 27	-0.085	0.058	-0.054	-1.476	0.140
ln(tv <sub>ol</sub> )*Operator No. 4	-0.041	0.029	-0.056	-1.423	0.155
Operator No. 18	0.167	0.134	0.031	1.249	0.212
Operator No. 26	-0.615	0.588	-0.102	-1.047	0.295
ln(tv <sub>ol</sub> )*Operator No. 10	-0.146	0.141	-0.055	-1.034	0.301
ln(tv <sub>ol</sub> )*Operator No. 27	-0.027	0.027	-0.037	-1.003	0.316
ln(tv <sub>ol</sub> )*Operator No. 13	0.030	0.034	0.029	0.873	0.383
ln(tv <sub>ol</sub> )*Operator No. 23	-0.028	0.038	-0.033	-0.737	0.461
ln(tv <sub>ol</sub> )*Operator No. 25	-0.204	0.276	-0.029	-0.737	0.461
Operator No. 1	0.080	0.120	0.032	0.668	0.504

SE = Standard error, SE Coeff = Standard error of the coefficient, t<sub>score</sub> = T-Test score, Sig. = Significance level, tv<sub>ol</sub> = tree volume under bark

Based on the estimates shown in Table 1, a productivity model that includes the influence of the different operators can be created. To simplify and qualify the model, only those estimates that are statistically significant are used. The horizontal line in Table 1 marks the threshold above which 29 of the multilinear regressions give parameter estimates that are significant at the  $\alpha = 0.05$  level, which can then be used to

describe the productivity model. Seventeen of the operators have a performance level significantly different from the mean model calculated using all the data. Therefore, the productivity of the other 15 operators can be described using the mean productivity model and their differences in performance can be explained by random variation in the data. Equation 3 shows the 17 calculated productivity models based on the dummy regression:

$$\ln(\text{Performance}) = 3.543 + 0.631 \cdot \ln(\text{tvol}) + \sum_{i=1}^{17} D_{\text{Operator}i} + \text{interaction terms}$$

	3.543	+	0.631	*	$\ln(\text{tvol})$		[0.04 < $\text{tvol}$ < 0.32]
+	(	-0.724	-	0.164	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}01}$ [0.04 < $\text{tvol}$ < 0.30]
+	(	-0.712	-	0.169	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}02}$ [0.04 < $\text{tvol}$ < 0.32]
+	(	-0.712	-	0.169	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}05}$ [0.05 < $\text{tvol}$ < 0.27]
+	(	0.113	-	0.166	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}07}$ [0.04 < $\text{tvol}$ < 0.32]
+	(	-0.363	-	0.166	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}08}$ [0.04 < $\text{tvol}$ < 0.32]
+	(	-0.639	-	0.156	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}09}$ [0.06 < $\text{tvol}$ < 0.20]
+	(	-0.796	-	0.241	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}11}$ [0.06 < $\text{tvol}$ < 0.32]
+	(	0.145	-	0.241	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}12}$ [0.04 < $\text{tvol}$ < 0.32]
+	(	-0.309	-	0.241	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}13}$ [0.05 < $\text{tvol}$ < 0.32]
+	(	-0.663	-	0.156	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}14}$ [0.06 < $\text{tvol}$ < 0.32]
+	(	0.179	+	0.086	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}15}$ [0.04 < $\text{tvol}$ < 0.32]
+	(	0.182	+	0.113	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}16}$ [0.04 < $\text{tvol}$ < 0.32]
+	(	0.176	+	0.113	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}18}$ [0.04 < $\text{tvol}$ < 0.32]
+	(	-0.977	-	0.275	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}21}$ [0.04 < $\text{tvol}$ < 0.32]
+	(	0.212	+	0.090	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}23}$ [0.05 < $\text{tvol}$ < 0.35]
+	(	-0.916	-	0.294	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}24}$ [0.05 < $\text{tvol}$ < 0.19]
+	(	-0.681	-	0.294	*	$\ln(\text{tvol})$	)* $D_{\text{Operator}28}$ [0.05 < $\text{tvol}$ < 0.32]

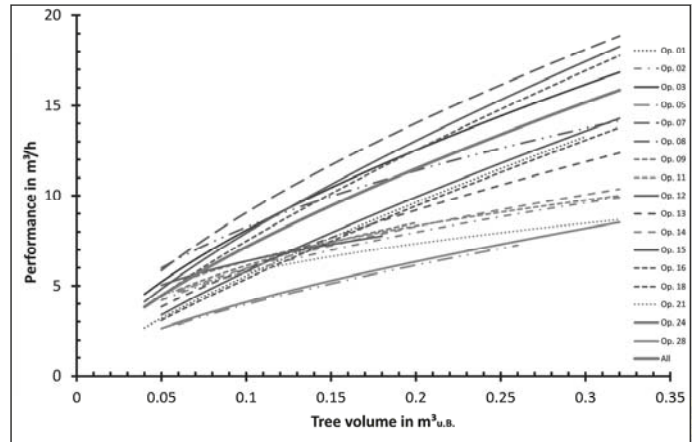
where  $\text{tvol}$  is the tree volume ( $\text{m}^3$  under bark) and  $D_{\text{Operator}i}$  is the dummy variable of Operator  $i$ . The productivity model only applies to the individual operator in the range of tree volumes shown in square brackets. Given the large number of parameters, the interpretation of the whole model is not trivial. The (transformed) mean model is given by an absolute value ( $3.543 \text{ m}^3/\text{PSH}_{15}$ ) and a value depending on tree volume ( $0.631 \cdot \ln(\text{tvol})$ ). The first number in each equation describes the absolute difference in performance from the mean; the second number describes the difference in the performance trend in terms of the tree volume.

Figure 3 is a graphical representation of the differences between operators. The solid line represents the mean performance of all operators irrespective of tree volume. This line joins all operators who do not differ significantly from the mean productivity model.

Relative to the mean performance level, the best operator works at a mean individual performance of 125%, and the worst operator at a mean individual performance of 56%. The minimum and maximum absolute values differ by a factor of 2.2, indicating that the fastest operator has a performance level more than twice that of the slowest operator.

The learning phases that inexperienced operators pass through are partly included in these calculations. In order to remove any bias in the data from this influence, and to be sure that only data from experienced operators (i.e. those with at least one year of operational experience) were analysed, data were deleted that pertained to the first 180 days of operations performed by inexperienced operators, and

**Figure 3.** Differences in productivity between the operators (dummy regression analysis) plotted against tree volume.



[3] relating to operators for whom there was no information about their expertise. This length of time seems to represent a reasonable compromise to encapsulate all the learning phases. Thus, it could be assumed that all data used to calculate the new dummy regression related to operators who had definitely reached the end of their individual learning phases (Purfürst 2010).

The result of the recalculation, with an adjusted coefficient of determination of  $\bar{R}^2 = 0.878$ , indicated that the operator with the highest productivity had a performance level of 122% of the mean, and the operator exhibiting the lowest productivity had a performance level of 69% of the mean. The minimum and maximum absolute values still differ by a factor of 1.8, which indicates that among experienced operators, the most productive operator is still nearly twice as productive as the least productive operator. This result agrees well with experiments that used only stem volume-based time-study data, which produced a similar ratio – 1:1.7 – between operators with the highest and the lowest productivities (Purfürst 2009). Even when only the central 80% of the data range (between the 10th and 90th percentiles) is analysed, there is still a ratio of 1:1.4 between the best and worst of the experienced operators.

This result underlines how large an influence the human factor has on productivity. It should also be pointed out that only mean values based on the stand level were used. If instead, single measurements without averaging had been used (the tree level), the values would have differed even more widely.

The multilinear dummy regression produced an adjusted coefficient of determination of  $\bar{R}^2 = 0.842$ . Thus, in the data used for the present analyses, 84% of the overall variation can be explained by the tree volume and the operator; this is a high proportion. It should also be noted that the arithmetic mean of stand productivities was used in the regressions, and this tends to give a higher coefficient of determination than when single tree data are used (Jacke 1980).

Co-variance analysis can be used to explain the sources of variation in the data. In this case, the operator, the tree volume and the interaction between them were used as independent

variables. Table 2 shows the analysis of scatter in the model within the interval  $0.04 \leq tvol \leq 0.32$ . The (transformed) tree volume has the greatest influence (45.9%). However, the influence of the operator also explains quite a large percentage (37.3%) of the variance. The interaction between operator and the tree volume only explains a small amount of the variance (1.4%), while the remaining 15.5% is due to residual variation.

**Table 2.** Analysis of scatter with co-variance analysis

Source	SS	Percentage	DF	AS	F	Sig.
ln(tvol)	251.1	45.9%	1	251.13	8,976.6	0.000
Operator	203.7	37.3%	32	6.37	227.5	0.000
Operator * ln(tvol)	7.8	1.4%	31	0.25	8.99	0.000
Residual	84.1	15.4%	3,006	0.28		
Total	546.8					

SS = sum of squares, DF = Degrees of freedom, AS = Average of squares

This large operator influence has generally been disregarded in the past.

## Discussion

### Operator influence

The influence of human actions is often, unlike tree volume, a very complex factor to analyse. The operator's performance, in turn, is the result of numerous factors that are not easily measured (e.g. tacit knowledge), and which can have yet further interactions with other variables (Nurminen et al. 2006, Ovasikainen 2005, Reichel 1997, Väättäinen et al. 2004a, 2004b).

Several previous studies have investigated the human impact on productivity. Harstela (1975) evaluated the level of human influence in motor-manual harvesting to be 56%, while Reichel (1997) found it to be considerably higher at 78%. In mechanical thinning, the influence of the human factor has been reported to be lower, at 43% (Siren 2001). The research presented here indicates that 37% of the variability in fully mechanized harvester work is due to differences between operators; this equates to three-quarters that of the influence of the main factor, the tree volume. However, the present research is based on simple working and environmental conditions. The more difficult the conditions, the greater the influence the human factor will have on productivity. However, as Ranta (2004) states: 'An effective driver can operate efficiently in all phases of the work cycle.'

Nevertheless, as this study identifies, even under simple conditions, this human factor has the second largest influence on productivity after the tree volume. This is in agreement with the results of Nurminen et al. (2006), Ovasikainen (2005) and Väättäinen et al. (2004a). Hence, as the human factor explains about two-fifths of the variation, it should be included in any model used to calculate harvesting productivity.

Kärhä et al. (2004) described how 'experienced' operators differ in their performance by up to 40%. In the study pre-

sented here, significantly larger differences were identified: up to 80%. If the operators' learning phase is included, these differences can increase further up to 120% – results that are significantly higher than those presented by Glöde (1999) of 20–50% and Ovasikainen (2005) of 40–55%. One reason for these discrepancies may be the sample size used in the various studies. For tests that consider maximum values, the 32 operators examined in the present study represent a relatively large sample size, and this can lead to the differences between minimum and maximum values being larger than they might be for small samples. By limiting the current analysis to data from only between the 10th and 90th percentiles, the differences found in present study were reduced to 40%, which is more comparable to the cited results of other studies.

However, the differences between the operators are not the same in every type of stand. Different stands present different working conditions, which also have an influence on the differences between the operators. For example, differences between operators are greater in first thinnings (Kärhä et al. 2004), with larger stems (Anonymous 2003), and in more difficult working situations (Väättäinen et al. 2004b).

The current trend within harvester research is the further automation of processes that will assist forestry workers. Examples are the automation of boom and head movements (Löfgren 2006), the development of (semi-) automated forest machines (Ringdahl 2008), and improving the harvesting process with remotely controlled machines such as the 'Beasten' (developed by Carlsson and Lennartson). The large-scale implementation of these concepts will take several more years (Hofmann 2004, Purfürst et al. 2007). Meanwhile, the results of the present study help us to understand better the general influence of machine operators and to simplify the planning of harvesting operations. As long as the Swedish vision: 'No man on the logs - No man on the ground - No man in the machine' (Löfgren 2004) is not a reality, the influence of the harvester operator has to be taken into account.

### Generalization of Statements

Work in the forest is usually characterized by complex, irreversible effects associated with a wide range of parameters. During the working process the raw material is changed and cannot be cut a second time. Moreover, it is necessary to isolate human factors from other factors that might influence harvesting productivity results. The present study, therefore, focused on uniform conditions, namely only first or second thinnings, and only pine-dominated stands in flat areas. Consequently, general conclusions drawn from the results are only valid in situations with conditions similar to those under which the data were generated. Despite the large degree of heterogeneity in environmental conditions that may occur in the forests, it is assumed that the relationships found in the present study are valid under a wide range of working conditions. However, it would be advisable to corroborate this hypothesis with further research.

There is also the question of the extent to which the subjects were actually selected from the population of harvester operators. Although the operators in the present study were chosen by a process that was as random as possible, at 32 the number of operators is still too small a sample from which to draw any definitive conclusions. Nevertheless, in the field of forest operations this sample should be considered sufficient to have provided useful results.

The study took place in Germany where harvester operators are, on average, younger and have more variation than other European operators. In addition, general factors such as working conditions, working hours, and the motivation of the harvester drivers differ greatly among different countries (Liden 2005). The condition of various regions may be different but variability in human work is often quite similar (Erler 1984). This seems to be the case for mechanized work. Nevertheless, it should be possible to generalize the results of the present study to other countries.

All available data used here were derived from CTL harvester thinnings. Critically, however, the transferability of these results to other types of harvesting (e.g. clear-cutting, storm damaged areas), and other types of machine (e.g. forwarders, skidders), needs to be assessed by means of time studies, operator assessment or analysing production documents. In analysing the influence of operators, the time aspect has not been fully considered. Operators whose production data incorporate those collected during their learning phase exhibit significantly poorer performance. The learning curve should, therefore, be considered in studies of this type (Purfürst 2010). Despite this, there remain large differences in harvesting productivity even among 'experienced' operators.

### Strengths and Limitations of the Study

The current study was designed to describe and quantify the influence of operators on productivity. Compared to most other operator-based studies, the number of operators included in the present study is relatively high, and the results should, therefore, be quite representative.

The large amount of information that was collected by the on-board computers allows the generation of accurate statistics from which statements regarding intra- and inter-individual variation in performance could be made. This information can be used not only for planning and cost calculations, but also in policy development and validation with respect to the training of harvester operators. However, the large dataset is linked to only limited information about the individual stand or tree that was actually harvested. Therefore, although the quantity of data in the present study is higher than in comparable studies, the quality of information relating to the associated environmental conditions is not as high as it has been in manual time studies.

The present study was based on historical logging data collated for every stand: the on-board computer used the arithmetic mean to summarize the harvesting data. This ignores the differences in time spent on harvesting operations as well as variations in tree diameters. It is well-known that, in most cases, the arithmetic mean is inadequate for making

accurate parameter estimates. Therefore, some statistical parameter estimates may contain unknown errors, and future data should relate to single trees rather than the whole stand. During the process of data capture in the present study, the storage capacity of the on-board computer was not always sufficient to save all tree-based data. However, with the current increase in the availability and reduction in cost of computer memory, storage space for data should no longer be a limitation.

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