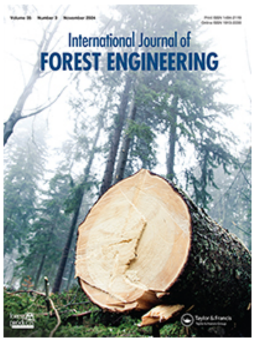


International Journal of Forest Engineering

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tife20

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**To cite this article:** Ola Lindroos, Jesper Pettersson & Tomas Nordfjell (2024) How stem size variations in forest stands influence harvester productivity and the use of productivity models, International Journal of Forest Engineering, 35:3, 389-398, DOI: 10.1080/14942119.2024.2387523

**To link to this article:** https://doi.org/10.1080/14942119.2024.2387523



Published online: 19 Aug 2024.

INTERNATIONAL JOURNAL OF FOREST ENGINEERING
2024, VOL. 35, NO. 3, 389–398
https://doi.org/10.1080/14942119.2024.2387523

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# How stem size variations in forest stands influence harvester productivity and the use of productivity models

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**ABSTRACT**

Stem size has the greatest effect on harvester productivity, and stem sizes vary in a forest stand. How these within-stand variations influence harvester productivity is normally not considered in studies or predictions of productivity. This study suggests reasons as to why the current production and/or application of productivity models are prone to bias from stem size variations in a stand, irrespective of whether models were developed from tree-based or stand-based studies. Moreover, it also provides empirical data on the stand stem size variation's influence on stand-based modeling of harvester productivity. Data from 11 harvesters in 347 final fellings and four harvesters in 80 thinnings were used. The mean productivity was 26.7 and 11.0 $m^3/PMh_5$ in final felling and thinning, respectively, and the mean stem size explained most of the observed variation. The productivity in final felling decreased with increased levels of stand stem size variation, as well as with increases in the proportion of broadleaf trees in the stand. For thinnings, productivity increased with increases in the proportion of pine trees in the stand, but there was no significant effect of stand stem size variation or other tested factors. The results show that stand stem size variation is a relevant factor to consider when modeling and predicting harvester productivity.

**ARTICLE HISTORY**
Received 5 March 2022
Accepted 23 July 2024

**KEYWORDS**
Time consumption; cut-to-length; Sweden; regression model

## Introduction

There are many uses for reliable harvester productivity models, the most obvious being the ability to plan and price harvesting for daily operations. Additionally, reliable models are also key tools for researchers in the evaluation of potential new machine types and harvesting systems.

It is a well-known fact that the work productivity (i.e. the volume produced per time unit) of harvesters is positively correlated to the size of the harvested trees, a relationship that explains most of the variation in productivity (e.g. Eriksson and Lindroos 2014; Liski et al. 2020; Ackerman et al. 2022). Various metrics have been used to describe tree size, including different types of stem volumes, stem masses or even diameter at breast height (1.3 m above stump height). For simplicity, the term stem size will be used from here on, since it is the merchantable part of the stem that most often is used to study harvester productivity.

There are two approaches to establishing the relationship between harvester productivity and stem size, using either individual trees or individual stands as observational units. When using individual trees as the observation unit, the tree's stem size (i.e. volume) divided by the time consumed when handling it gives the productivity, with the stem volume being used to explain how the productivity varies between trees. This can be done based on trees within a stand, or by pooling trees from several stands.

When using individual stands (or parts of stands) as observational units, the time consumption required for each stand divided by the harvested volume gives the (mean) productivity in the stand, with the mean stand stem size being used to explain how the productivity varies between stands.

Both approaches are normally used with the aim of producing models capable of predicting the productivity in stands that will be harvested, and with the stand's mean stem size (e.g. arithmetic stem volume) as input. Hence, models based on individual trees or individual stand means are used to estimate productivities in unharvested stands based on their mean stand stem sizes. This procedure facilitates the application of models, since a single value is needed to ascertain the influence of stem sizes on the harvesting work in the stand. Although this is convenient in terms of its minimal data requirements for using the model, the procedure ignores the possible effect of stem size variation in the stand. Moreover, the procedure appears to have developed from a perceived need to handle practical limitations in data availability and possibly computing capacity, and not from a scientific, or even logical, basis.

A certain level of variability in stem size can be expected in all stands but might be especially accentuated in seminaturally managed forests, where regeneration and ingrowth of other species commonly occurs. In contrast, short-rotation plantation stands might have more uniform stem sizes due to rationalization that is not available in more natural forest management regimes (Ackerman et al. 2022). The effect of stem size variations in a stand was known in early studies of motor-manual felling and processing (e.g. Ager 1967) and was included in the Swedish company Stora Skog's (now Stora

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Enso) productivity models for harvesters in final felling in the early 1990s (Stora Skog 1991). However, to the best of the authors' knowledge, the effect of stem size variation in a stand on harvester productivity has not been addressed since then and has not been found in any international scientific, peer-review publications. The exception is the theoretical study by Ackerman et al. (2024), inspired by the MSc thesis this paper builds upon (Pettersson 2017) and published at the end of the lengthy publication process of this paper. Hence, stand stem size variation warrants further investigation, irrespective of whether tree-based or stand-based models are used.

## *Tree-based productivity models*

Tree-based models are by far the most common models used to describe harvester productivity and are therefore also commonly used to predict the expected productivity of an unharvested stand. When using tree-based productivity models with a stand's mean stem size to predict the mean productivity in the stand, the underlying assumption that justifies such an application is that there is no variation in stem sizes in the stand or that the variation will not cause any estimation errors. The former assumption is easily refuted by most stands, but the latter might be less straightforward to understand and investigate. Why might stand stem size variations have an effect on productivity? Since the productivity depends on the average time required to handle the stems in the stand, the possible effect depends on the relationship between time consumption and stem size. If the relationship is linear, there is no effect of stem size variation within the stand, since the time consumption will change in direct proportion to the stem size. In other words, the extra time required to handle larger-than-average stems will be compensated for by the lesser amount of time taken to handle the stems that are smaller than average. However, if the relationship is non-linear, there will be an effect since the difference between smaller-than-average and larger-than-average stems will not even out. How great the effect will be depended on the level and distribution of the variation, as well as on the properties of the non-linear relationship.

To demonstrate this possible effect, the hypothetical time consumption relationships, shown in Figure 1, can be used. One relationship is linear and the other is quadratic, but both give identical time consumptions at a stem volume of 0.35 m$^3$. However, time consumptions from the quadratic relationship are slightly higher for stem sizes both lower and higher than 0.35 m$^3$. We assume that these relationships were established by some conventional time studies (i.e. tree-based models) and are now used to predict the time consumption in two (for pedagogic reasons, unrealistic) stands, both with a mean stem size of 0.35 m$^3$. However, the variation in stem sizes is fundamentally different. All stems are identical (0.35 m$^3$) in the first stand whereas, in the other stand, half of the stems have a stem size of 0.1 m$^3$ and the other half 0.6 m$^3$. By using the two stands' mean stem sizes for the prediction, all four combinations of stands and relationships will yield the same value (25.1 m$^3$/h). However, when applying the relationships to the stem sizes that actually exist in the stand, there are substantial differences between the combinations. When using the linear relationship, the calculated time consumption, and the resulting productivity, is unaffected – it remains identical for both stands (25.1 m$^3$/h). Thus, the variation in stem sizes does not matter with a linear relationship. However, with the quadratic relationship, the time consumption for stand two is 9% higher than for stand 1. Thus, the productivity will be 23.0 m$^3$/h (i.e. 9% lower) in the stand with a large variation in stem sizes. This is logical, since this example stand contains only stems that take longer to handle than indicated by the stand's mean size. Other distributions of stem sizes and other relationships will naturally generate other effects on the productivity, as shown on real stand data in Ackerman et al. (2024).

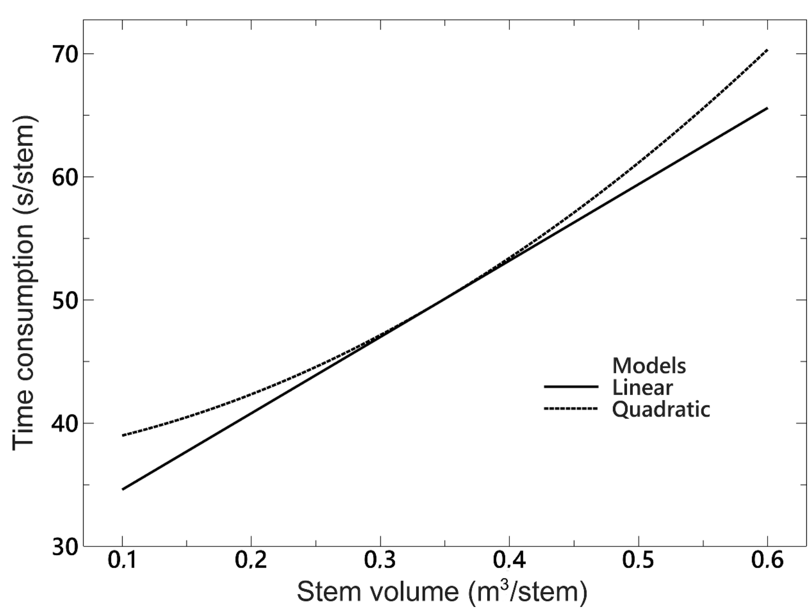


**Figure 1.** Hypothetical models for predicting a harvester's required work time per stem as a function of the stem's volume. Both models give identical time consumption at a stem volume of 0.35 m$^3$. The linear model is $y = 28.4 + 62\times$ and the quadratic model is $y = 37.1 + 11.6\times + 73x^2$.

A linear relationship between time consumption per stem and stem size is related to the specific shape of the productivity curve, whereas similar but slightly different productivity curves result in (or originate from) relationships that are non-linear. Many empirical studies that have provided tree-based productivity models have used a wide variety of relationships between productivity and stem size: linear (e.g. Sirén and Aaltio 2003), quadratic (e.g. Nurminen et al. 2006), power (e.g. Jiroušek et al. 2007), logarithmic (e.g. Strandgard et al. 2013) and various complex non-linear functions (e.g. Visser and Spinelli 2012; Ackerman et al. 2022). What these many models have in common is that the harvester productivity, in general, increases at a decreasing rate with increasing stem size. Moreover, most productivity models are more or less linear within limited ranges of stem sizes. However, it has also been shown that, at some point, the productivity reaches a maximum and starts to decline, due to the stems becoming too large to handle. For instance, Visser and Spinelli (2012) found that the productivity peaked at a mean stem size of about 1 $m^3$ for the studied purpose-built harvesters and at about 2.5–3 $m^3$ for excavator-based harvesters. The variation in productivity model shapes can originate from many different sources, such as variations in work and stand characteristics, as well in data analysis methods. The (re)transforming of the many shapes of productivity models to the relationship between the time consumption per stem and the size of the stem shows that there is a large variation in shapes (Figure 2). In other words, the vast variation in empirical studies indicates that the time consumption per stem is unlikely to always be linear. Hence, the process of using tree-based models to predict productivity in a stand based on its mean tree size is likely to carry a risk of estimation errors.

### *Stand-based productivity models*

Stand-based productivity models can be produced by manual data-gathering (e.g. Mederski et al. 2016; Strandgard et al. 2016), but the gathering of sufficient numbers of observations is laborious. This is most likely one major reason to why stand-based models have been rather rare in the past. However, advances in automatic gathering of follow-up data (e.g. Kemmerer and Labelle 2020) have facilitated stand-level data gathering. As a result, many stand-based models have been published in the past decade (e.g. Purfürst and Erler 2011; Gerasimov et al. 2012; Eriksson and Lindroos 2014; Olivera et al. 2016; Liski et al. 2020). By using this approach, the effect of stem size variation within stands is included in the creation of the model. When applying stand-based models to predict productivity based on a stand's mean stem size, the underlying assumption justifying such use is that the stand's stem size variation will not cause any estimation errors. The stem size variation in the stands the model is based on is included in the model, but it might differ from the variation in stands that the model is applied to. Moreover, the stand stem size variation has, to the best of our knowledge, hitherto not been empirically quantified and tested for its possible effect on harvesters' mean productivity. If there is an effect, the stand stem size variation could be included in the stand-based model when being applied to stands with different stem size variations.

There are some logical explanations for why stand stem size variation has been handled in an overly simplistic way when trying to predict harvester productivity, irrespective of the modeling approach. One might be the tacit belief that stand stem size variations are irrelevant. This seems, however, highly unlikely. A more likely explanation is that only a decade ago, information on stand stem size variations was scarce and costly to acquire. However, the rapid development in remote sensing has provided high-resolution data on the individual stems in the stand (e.g. Lindroos et al. 2015; Noordermeer et al. 2021). Much of the required information may already be currently available at a low cost and be even more available and more accurate in the near future.

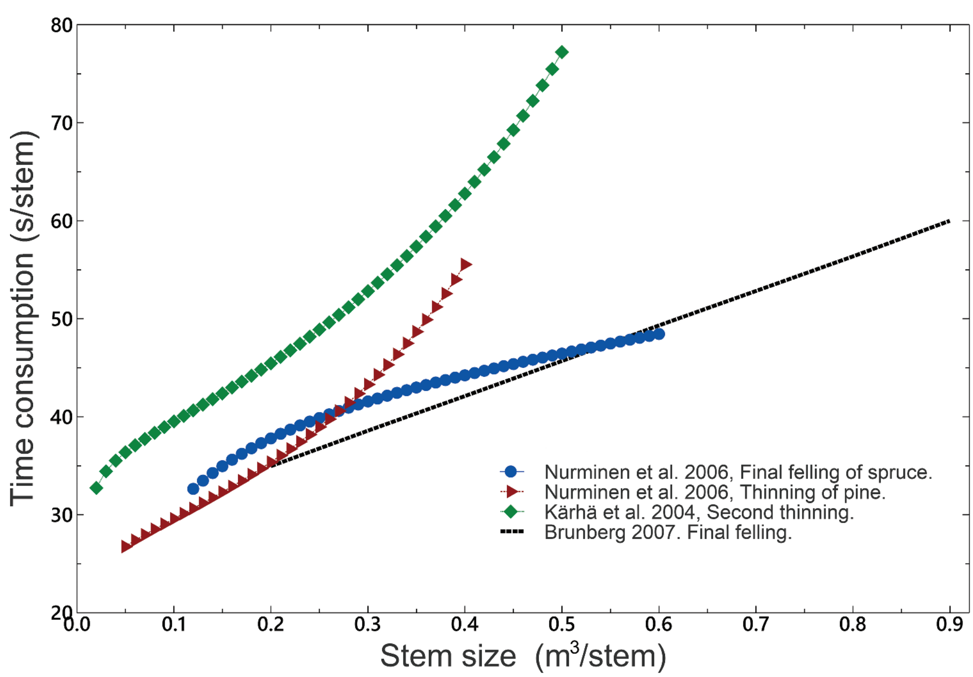


**Figure 2.** Examples of variation in model shapes when (re)transforming tree-based productivity models to time consumption per stem.

That stem sizes vary in forest stands is a well-known fact, although the variation differs due to, for instance, management regimes (Ackerman et al. 2024). The variation will influence harvester productivity unless the time consumption required to handle a stem is linearly correlated to the stem size as shown and discussed by Ackerman et al. (2024). The many examples above indicate that the relationship might not be linear. Therefore, the question is whether or not stand stem size variation should be included when predicting harvester productivity. Since the effect of stand stem size variation has not been studied empirically for many decades, the first step is to investigate whether or not stand stem size variations have any observable effect on productivity in real-life work.

Therefore, the aim of the study was to evaluate whether or not there is an effect of stem size variation in stands on harvester productivity. A secondary aim was to provide representative models for harvester work in conventional final fellings and thinnings in northern Sweden, with several levels of complexity to enable practical usage with different levels of available input variables.

## Materials and methods

The contribution of stand stem size variation to models for predicting harvester productivity was analyzed using data gathered from a forest company's IT-system. These data were routinely gathered follow-up for their logging operations. All wood volumes mentioned in the following text, figures and tables refer to under bark volumes of solid stems, after cutting their tops at a small end diameter of 5 cm under bark. All work times refer to productive machine hours, with delays shorter than 5 minutes included ($PMh_5$). This study was based on data from the Master's thesis of Pettersson (2017).

### *Productivity and stand data*

The dataset used for the analyses was created from three different sources of data, all originating from normal harvester work between April 2014 and October 2016 by the Swedish forestry company Holmen Skog AB (called Holmen). The data were collected from harvesters owned by Holmen, and which were operated at approximate latitudes 62°–66° in Sweden (in Holmen's Northern Region). Holmen's operations are carried out in managed forests, owned by the company itself or by private individuals who engage Holmen for their forest management needs. The forests are dominated by Scots pine (*Pinus sylvestris*) and Norway spruce (*Picea abies*), with some intermixed hardwoods, mainly birch (*Betula spp.*) and aspen (*Populus tremula*). Forests that were subject to several selection cuttings until the mid-20th century are now normally subjected to final fellings, while thinnings are generally used in forests planted between 1950 and 1970. Harvest operations were carried out in compliance with legal requirements and the company's environmental standards.

In total, data from 11 harvesters in final felling and four harvesters in thinning were included in the dataset. The size of the machines varied from 15.8 to 22.3 tonnes (t). They had been used for 347 final felling (567,294 $m^3$) and 80 thinning (45,098 $m^3$) operations.

The Harvesters typically used during the study period included the Komatsu 931 and 951, and the John Deere 1270 for final felling, and the Komatsu 901 and John Deere 1070 and 1170 for thinning. However, many machines were not exclusively used in either thinning or final felling (Table 1).

The dataset was compiled by merging data from three different sources. As part of their normal routines, Holmen collected follow-up data for their own machines, which were used as the source for the work carried out (work time, volumes, mean stem sizes, etc., see Table 2) and were based on data registered by the harvesters' onboard computers. Information relating to stand features and assortments was collected from Holmen's system for wood supply management (VSOP). Both these two data sources were extracted from Holmen's IT systems. However, in order to find out the variation in stem sizes within stands, additional data had to be used. Stem files were automatically generated during the harvester's work (StanForD 2010) and contained all stems harvested in a stand. In Sweden, those files are transferred to, and handled by, the economic association Biometria (at the time of data collection called Skogsbrukets Datacentral (SDC)), the Swedish forest industry's information hub for supply chain data. Thus, stem files for the harvested stands were collected from SDC by using the PRINS software. In the available files, individual stem volumes were not recorded in such a way that they could be used to evaluate variations in stem volumes. Instead, the information on the harvested stems' diameter at breast height (DBH, i.e. at 1.3 m height) was used as an indication of stem size variation, since such data were available.

**Table 1.** Harvester machine data and harvested volumes.

| | | | | Number of harvesting sites (n) | | Total volume ($m^3$) | |
|---|---|---|---|---|---|---|---|
| Brand | Model | Multi-tree handling head | Total weight (t) | Final felling | Thinning | Final felling | Thinning |
| John Deere | 1070E | Yes | 15.8 | 4 | 20 | 1,254 | 11,402 |
| Komatsu | 901 tx | Yes | 16.7 | 39 | 30 | 31,427 | 19,499 |
| John Deere | 1170E | Yes | 17.9 | 8 | – | 6,237 | – |
| Eco-log | 560D | Yes | 18.6 | 20 | 24 | 9,490 | 13,117 |
| Komatsu | 931 | Yes | 19.6 | 65 | – | 141,007 | – |
| Komatsu | 931 | Yes | 19.6 | 63 | 6 | 98,490 | 1,080 |
| John Deere | 1270E | Yes | 20.5 | 48 | – | 96,715 | – |
| John Deere | 1270E | No | 20.5 | 27 | – | 27,155 | – |
| John Deere | 1270E | Yes | 20.5 | 43 | – | 83,699 | – |
| Komatsu | 951 | Yes | 22.3 | 23 | – | 53,308 | – |
| Komatsu | 951 | Yes | 22.3 | 7 | – | 18,512 | – |
| *All pooled* | | | | *347* | *80* | *567,294* | *45,098* |

**Table 2.** Stand variables that were tested as independent variables for the productivity models. The total dataset contained 347 and 80 harvester operations in final felling and thinning, respectively.

| | | Final felling | | | | Thinning | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Unit | n | Mean | SD | Range | n | Mean | SD | Range | Data capture[a] |
| Mean stem size of harvested stems | $m^3$ | 347 | 0.234 | 0.080 | 0.066-0.538 | 80 | 0.090 | 0.272 | 0.042-0.185 | F |
| Harvested volume | $m^3$/ha | 342 | 172.5 | 57.89 | 41.6-481.5 | 80 | 44.0 | 19.1 | 5.4-121.7 | F/V |
| Total harvested volume | $m^3$ | 347 | 1635 | 1513 | 50-9512 | 80 | 562.5 | 417.3 | 52.3-2127.5 | F |
| Harvested trees | n/ha | 342 | 779 | 251 | 119-1627 | 80 | 499 | 204 | 59-1189 | F/V |
| Bucked assortments[b] | n | 333 | 3.8 | 1.1 | 1-7 | 79 | 4.1 | 1.3 | 1-8 | S |
| Bucked main assortments[c] | n | 332 | 2.3 | 0.7 | 1-4 | 79 | 1.6 | 0.7 | 1-3 | S |
| Proportion of trees | | – | – | – | – | | | | | |
| –Pine | % | 347 | 35.7 | 26.4 | 0-99.5 | 80 | 54.4 | 31.4 | 0.3-99.0 | S |
| –Spruce | % | 347 | 50.9 | 23.8 | 0.4-99.3 | 80 | 26.0 | 19.9 | 0.4-91.3 | S |
| –Broadleaves | % | 347 | 13.3 | 9.9 | 0-54.3 | 80 | 19.9 | 19.9 | 0-98.8 | S |
| Proportion of tree accumulation | | | | | | | | | | S |
| –All trees | % | 347 | 4.36 | 4.91 | 0-30.1 | 80 | 12.1 | 12.9 | 0-92.1 | S |
| –Pine | % | 347 | 1.1 | 2.7 | 0-28.1 | 80 | 6.6 | 11.6 | 0-82.3 | S |
| –Spruce | % | 347 | 2.7 | 3.2 | 0-23.0 | 80 | 3.8 | 4.7 | 0-24.0 | S |
| –Broadleafs | % | 347 | 0.5 | 1.3 | 0-10.4 | 80 | 1.7 | 2.5 | 0-12.8 | S |
| CV[d] | % | 347 | 37.0 | 4.2 | 23.6-49.7 | 79 | 30.4 | 4.5 | 20.1-44.4 | S |

SD = standard deviation. [a]F = Follow-up data; V = data from the supply management system VSOP; S = data from stem files. [b]All assortments, irrespective of volume. [c]Assortments that constituted at least 15% of the total harvested volume. [d]Coefficient of variation for breast height diameter of harvested stems (i.e. standard deviation/mean value × 100).

However, some generalizations had to be made, due to how individual DBHs were aggregated into categorical data in the form of a number of observations in 20-mm-wide DBH classes. Classes with a DBH below 80 mm were excluded from the analyses, since those were too small to constitute merchantable logs, and should actually not have been harvested. For the remaining stems, the distributions over the DBH classes were "retransformed" to continuous data by giving the lowest class value to all stems in that class (i.e. all stems in the DBH class 120–139 mm were assumed to have a diameter of 120 mm). The allocation of individual DBHs to all harvested stems enabled the arithmetic mean DBH and the standard deviation to be calculated for a stand. Subsequently, the coefficient of variation (CV) for the DBH was calculated for each stand, by dividing the standard deviation by the mean value and multiplying by 100 to obtain the percentage value. Subsequently, the CV for the DBH was used as an indication of a stand's variation in stem size.

Moreover, the stem files enabled the compilation of data on the proportion of stems that were harvested by use of the harvester head accumulating function (which most harvesters had) over tree species, and also the species proportions of the total number of harvested stems.

In total, all variables in Table 2 were used in the analysis, some of which were combined in the analysis to evaluate possible interaction effects. Most of the variables from the conventional follow-up data were in their original reported form, or calculated from data within the respective data sources (e.g. productivity which was calculated by dividing the harvested volume by the work time, both from the follow-up reports), whereas stand densities ($m^3$/ha and trees/ha) were derived by combining the harvested volume and trees from the follow-up reports with the area found from the supply management system VSOP. A categorical variable was created to indicate the machine size, with harvesters with a mass of 17–20 metric tonnes being classified as middle-sized harvesters, whereas lighter machines and heavier machines were classified as small-sized and large-sized machines, respectively (cf. Table 1).

To obtain a representative and useful dataset, the occurrence of unrepresentative stands and missing or unreliable data had to be handled. In general, the information from the follow-up system for, in particular, the harvested volume and work time proved to be reliable since it was the basis for cost transactions. However, other data were, to some extent, less reliable. Prerequisites for a stand to be included in the analysis were that it was reasonably representative of conventional operations. Thus, stands in which less than 50 $m^3$ in total had been harvested were excluded, as were also stands which were categorized as being subject to untypical operations (e.g. harvest of seed trees and windthrow salvage logging). Stands with missing data for work time or harvested volume were also excluded, as well as stands for which no stem files were available. For some stands, the stem files contained fewer stems than recorded in the follow-up data. Due to the possible influence on CV calculations, stands were excluded if the stem files contained less than 75% of the number of stems reported in the follow-up data.

After those removals, the dataset comprised 347 stands of conventional final fellings with mostly complete data (cf. Table 2). The only data missing were for the number of assortments and the number of main assortments, for which 14 and 15 stands, respectively, missed data for the final felling. Moreover, for one stand, the area was missing and there were also indications of some inaccuracies related to the difficulty in correctly estimating the actual harvested area which might deviate from the stand's area (including nonproductive land, ecological set-asides etc.). In the two final felling stands, the data indicated a harvest of very few trees (<50 trees/ha) but normal productivities (22 and 25 $m^3/PMh_5$ at mean stem sizes of 0.21 and 0.24 $m^3$, respectively). Among the two others, the indicated harvest of >3900 trees/ha was more than twice as much as for any other stand in the study (Table 2). Thus, the area-based data for the four stands were considered to be erroneous, so values for trees per hectare and harvested volume per ha were removed but all other data for those stands were kept intact. Similarly, an outlier for the CV values in thinnings was also removed. In that case, the stand had a mean stem size of 0.052 $m^3$, a volume of 262 $m^3$/ha, a productivity of 4.9 $m^3$/$PMh_5$, with 71% of the trees being broadleaves and 23% spruce. It may well be that it was a two-storage stand which resulted in a correctly calculated, but very high CV. However, the stand was considered to be too untypical in regard to CV, since its calculated CV value of 77% was almost twice as high as the maximum of the other thinnings (44%). Therefore, the CV observation was removed, but all other data for the stand were kept intact.

In the follow-up data available for this study, the registered work time (including delays shorter than 5 minutes) was classified into three classes: productive work time, relocations (by driving the harvester between stands, and not by trailer) and other work time. The productive work time constituted, on average, 97.8% (SD 4.7) and 97.5% (SD 3.8) of the work time registered for operations in final felling and thinning, respectively. Correspondingly, relocations constituted 1.0% and 0.9% (SD 3.1 and 2.3, respectively), and other work time constituted 1.2% and 1.6% (SD 3.7 and 3.3, respectively). In these analyses, only the productive work time was used. It should also be noted that the available data did not allow for a transformation to delay-free productivity ($m^3$/$PMh_0$) due to a lack of information about the amount of delays shorter than 5 minutes. It also did not allow for transformation to scheduled machine time (SMh), including all delays as well as all types of work, due to a lack of information about delays as well as possibly unrecorded miscellaneous work.

### Statistical analysis

The statistical analysis focused on exploring the possible effect of stem size variation in stands (by analyzing the effect of CV) on harvester work in conventional final fellings and thinnings. This was addressed by analyzing the CV's contribution to models for predicting machine productivity using linear regression based on an ordinary least squares (OLS) parameter estimation. Ordinary models for harvester productivity, representative for final fellings and thinnings in Northern Sweden, were developed, and whether CV contributed in relation to other contributing variables was tested.

Productivity models are likely to be used for diverse practical situations, in which varying degrees of input variables are available. Therefore, models with varying degrees of complexity were developed. The simplest models included variables well known to influence harvester productivity and the other models were based on a combination of a priori knowledge and examination of the data.

In order to meet the OLS assumptions of linearity, independence, homoscedasticity and normality of residuals, some data included in the study were transformed to their natural logarithms (Ln) during the analyses. Results from the models developed thus needed to be retransformed and corrected for logarithmic bias to be applicable to real-life situations. A common method for correcting a model's logarithmic bias is to add ($RMSE^2$)/2 to the intercept before the retransformation (Baskerville 1972; Zeng and Tang 2011), which was done when the models were visualized. Pearson's test was used to analyze correlations between variables. All the analyses were carried out using Minitab 18 (Minitab Inc., USA) with the critical significance level set to 5%.

## Results

### Final felling

The mean of harvester productivity in final felling was 26.7 $m^3$/$PMh_5$ (SD 8.2, median 25.8, range 7.8–65.0). Productivity and mean stem size were transformed to meet regression analysis assumptions. As expected, the mean stem size explained most of the observed variance ($R^2$-adj >61%) in final felling (models *i* in Table 3). Productivity increased with mean stem size or its square product, but, when including both simultaneously, the mean stem size did not contribute to the model ($p = 0.298$). Hence, in the further analysis, the square product of the mean

**Table 3.** Models for harvester productivity in final felling, based on data from 347 harvesting operations. Variable units are provided in Table 2.

| Model category | Variable | Parameter estimate | Standard error | p-value | VIF | $R^2$-adj (%) | RMSE |
|---|---|---|---|---|---|---|---|
| i-1 | Full model | – | – | <0.001 | – | 61.13 | 0.19 |
| | Intercept | 4.2949 | 0.0465 | <0.001 | – | | |
| | Ln(Mean stem size) | 0.6992 | 0.0299 | <0.001 | 1.00 | | |
| i-2 | Full model | – | – | <0.001 | - | 61.69 | 0.19 |
| | Intercept | 3.7752 | 0.0250 | <0.001 | - | | |
| | $(\text{Ln(Mean stem size)})^2$ | −0.22329 | 0.00945 | <0.001 | 1.00 | | |
| ii | Full model | – | – | <0.001 | - | 62.79 | 0.19 |
| | Intercept | 3.7883 | 0.0249 | <0.001 | – | | |
| | $(\text{Ln(Mean stem size)})^2$ | −0.2071 | 0.0105 | <0.001 | 1.27 | | |
| | Proportion of broadleaf trees (%) | −0.00390 | 0.00116 | 0.001 | 1.27 | | |
| iii | Full model | – | – | <0.001 | - | 62.64 | 0.19 |
| | Intercept | 4.0511 | 0.0917 | <0.001 | – | | |
| | $(\text{Ln(Mean stem size)})^2$ | −0.21945 | 0.00941 | <0.001 | 1.02 | | |
| | CV | −0.00771 | 0.00247 | 0.002 | 1.02 | | |
| iv | Full model | – | – | <0.001 | - | 63.35 | 0.19 |
| | Intercept | 4.0094 | 0.0921 | <0.001 | - | | |
| | $(\text{Ln(Mean stem size)})^2$ | −0.2066 | 0.0104 | <0.001 | 1.27 | | |
| | Proportion of broadleaf trees | −0.00327 | 0.00118 | 0.006 | 1.33 | | |
| | CV | −0.00623 | 0.00250 | 0.013 | 1.07 | | |

VIF = Variance inflation factor; R2-adj = adjusted level of explained variation; RMSE = Root mean square error; CV = Coefficient of variation for breast height diameter of harvested stems. Note: Models are for Ln(y), where y = productivity in $m^3$/$PMh_5$. The coefficient (intercept) is not corrected for logarithmic bias, and should thus be increased by $RMSE^2/2$ when estimating y. For instance, when using model *i-2*, the productivity is estimated by the equation $y = \exp(3.7752 + 0.19 \times 0.19/2 - 0.22329 \times (\text{Ln(mean stem size)})^2)$.

stem volume was used. The retransformed productivity (estimated according to model *i-2*) increase declined (curve linearly) with increases in mean stem sizes (Figure 3). Of the other variables in Table 2, it was only the proportion of broadleaf trees and the CV that significantly contributed when being added to model *i-2*. Productivity decreased with increases in the proportion of broadleaf trees as well as with increased CV, respectively, in the stand (models *ii* – *iv*). The inclusion of the proportion of broadleaf trees and CV, individually or together, increased the $R^2$-adj level by about 1–2% units (models *i* – *iv* in Table 3).

The actual effect on productivity of CV as well as by the proportion of broadleaf trees was rather modest. When using model *iii* and the average mean values for stem size, CV and proportion of broadleaf trees in the final felling data (see Table 1), the productivity decreased from 27.6 to 26.7 $m^3/PMh_5$ (i.e. 3.2%) when the CV level was increased by 5% units. Decreasing the CV level by 5% units increased the productivity by 3.2%. Correspondingly, an increase in the proportion of broadleaf trees by 10% units resulted in a productivity decrease of 4.3%, whereas a decrease by 10% units resulted in a productivity increase of 4.3%.

Harvester size classes contributed significantly to the models, but a high variance inflation factor indicated covariation with another factor in the model. Indeed, it was found that the harvester sizes had been working in stands with significantly different mean stem sizes (Tukey test, $p < 0.001$), with average mean stem sizes of 0.18, 0.23 and 0.26 $m^3$ for the small, medium and large-sized harvesters, respectively. When considering those differences by including the interaction between the harvester size and mean stem size, the interaction did not significantly contribute to the regression models *i* – *iv*. Thus, harvester size classes were not considered in the models.

There was significant variation in productivity between the 11 individual harvesters in the data. When excluding the harvesters with less than 10 observations and then adding harvester as a categorical variable to the regression models *i* – *iv* (new $n = 328$, over 8 harvesters), the level of explained variation increased by approximately 13% units ($R^2$-adj ≥74.4%).

The productivity decreased with increased CV also for individual harvesters. However, the effect of CV on productivity varied between the harvesters in the data, by adding between 0.1722 and 0.9223 to the intercept of model *iii* (adding the interactions between harvesters and CV to model *iii*, with $p \leq 0.005$ for all interactions and model's $R^2$-adj = 77.9%) (data not shown).

### *Thinnings*

The mean of harvester productivity in thinnings was 11.0 $m^3/PMh_5$ (SD 3.3, median 10.6, range 4.8–21.6). Regression analysis assumptions were met without Ln transformation of productivity and mean stem volume. As expected, the mean stem size explained most of the observed variance ($R^2$-adj >56%) in thinning (models *i* – *ii* in Table 4). Productivity increased with mean stem size, and/or its square product. Including both simultaneously yielded a high $R^2$-value but with an insignificant contribution of the intercept and a significant, but rather high, p-value for the square product of the mean stem size. In fact, when testing the contribution of other variables, the removal of the square product of the mean stem volume yielded better models. Within the data range, the productivity increased linearly with increases in mean stem sizes (Figure 3). Of the other variables in Table 2, it was only the proportion of pine trees and the number of bucked assortments that significantly contributed to the model. Productivity increased with increases in the proportion of pine trees in the stand (model *iii*), but the actual effect on productivity was rather modest. At

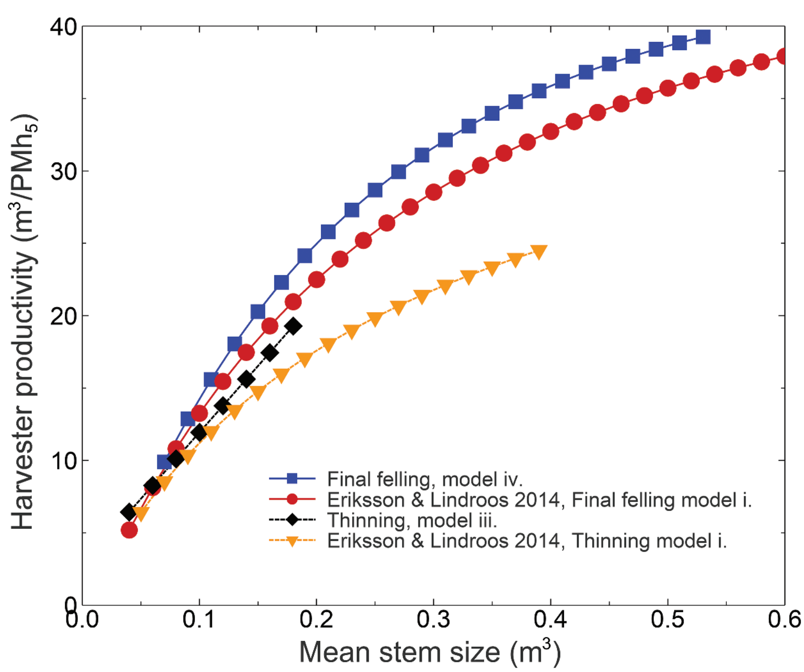


**Figure 3.** Harvesting productivity in final felling and thinning as predicted by models presented in Tables 3 and 4. Mean values have been used for the variables CV, proportion of broadleaf trees and proportion of pine trees (cf. Table 1). Predicted productivity is presented together with predictions obtained from Eriksson and Lindroos (2014), which are in delay-free machine time ($m^3/PMh_0$).

Table 4. Models for harvester productivity in thinning, based on data from 80 harvesting operations. Variable units are provided in Table 2.

| Operation | Model category | Variable | Parameter estimate | Standard error | p-value | VIF | $R^2$-adj (%) | RMSE |
|---|---|---|---|---|---|---|---|---|
| Thinning | i-1 | Full model | – | – | <0.001 | – | 62.35 | 2.04 |
| | | Intercept | 2.305 | 0.794 | 0.005 | – | | |
| | | Mean stem size | 96.85 | 8.440 | <0.001 | 1.00 | | |
| | i-2 | Full model | – | – | <0.001 | – | 55.67 | 2.21 |
| | | Intercept | 7.278 | 0.449 | <0.001 | – | | |
| | | (Mean stem size)$^2$ | 424.1 | 42.4 | <0.001 | 1.00 | | |
| | ii | Full model | – | – | <0.001 | – | 64.02 | 2.00 |
| | | Intercept | −2.07 | 2.18 | 0.345 | - | | |
| | | Mean stem size | 187.3 | 42.8 | <0.001 | 26.97 | | |
| | | (Mean stem size)$^2$ | −426 | 198 | 0.035 | 26.97 | | |
| | iii | Full model | – | – | <0.001 | – | 64.81 | 1.97 |
| | | Intercept | 1.758 | 0.797 | 0.030 | – | | |
| | | Mean stem size | 91.74 | 8.40 | <0.001 | 1.06 | | |
| | | Proportion of pine trees (%) | 0.01853 | 0.00729 | 0.013 | 1.06 | | |

VIF = Variance inflation factor; $R^2$-adj = adjusted level of explained variation; RMSE = Root mean square error; Note: Models are ordinary linear models, where y = productivity in $m^3/PMh_5$. For instance, using model i, the productivity is estimated using the equation y = 2.305 + 96.85×mean steam size.

the average mean stem size and pine proportion in the thinning data (see Table 1), the productivity increased from 11.0 to 11.9 $m^3/PMh_5$ (i.e. 8.2%) when the proportion of pine trees was increased to 100%. If the proportion of pine trees was set to 0%, the productivity decreased to 10.0 $m^3/PMh_5$ (i.e. by 9.1%).

When adding the number of main bucked assortments as categorical data to model *iii*, it was found that increases in assortments significantly ($p < 0.012$) contributed to higher productivity with more than 1 $m^3/PMh_5$ and assortment. This contradictory effect was further scrutinized. When included in model *iii*, the assortments did not result in high variance inflation factor values (≤1.47). Nevertheless, there was a significant difference in mean stem size between the three groups of number of bucked assortments ($p < 0.001$), with more assortments bucked in stands with larger stem sizes. When considering those differences by including the interaction between the number of bucked main assortments and the mean stem size, the interaction did not significantly contribute to the regression models *i* – *iii*. Thus, the number of bucked main assortments was not considered in the models.

When excluding the harvesters with less than 10 observations and then adding harvester as a categorical variable to the regression models *i* – *ii* (new $n = 71$, over 3 harvesters), the level of explained variation increased approximately 15% units ($R^2$-adj ≥78.8%).

## Discussion

The productivity levels found in the current study are in line with, although slightly higher than, the productivity levels described by Eriksson and Lindroos (2014) from the same geographical region (Figure 3). The difference might be due to the results of the current study being based on circa 5 years of more recent harvest operations since the productivity levels have historically increased with time (Eriksson and Lindroos 2014).

As expected, the productivity increased significantly with mean stem size without any sign of reaching a maximum point. This is in line with published studies when stems are not too big to handle (cf. Figure 3) (Visser and Spinelli 2012). Another significant result was that the productivity decreased with an increased proportion of broadleaf trees. This is also in line with previous research (e.g. Brunberg 1997) and is likely because broadleaf trees are often more crooked and have branches that are more difficult to delimb than coniferous trees. Such features result in lower productivity (e.g. Labelle et al. 2016; Mederski et al. 2022) and are sometimes addressed in models, but by allocating them to specific tree types (e.g. the proportion of “difficult trees” in Eriksson and Lindroos (2014)).

There was a significant variation in productivity among most of the individual harvesters in the data. When adding individual harvesters as a categorical variable, the level of explained variation increased to at least 74%. We do not have any information about the operators in the data, but different operators operated the different harvesters. Hence, the difference between the individual harvesters is due to a combination of different machine-specific performance (e.g. Ackerman et al. 2022) and operator-specific performances (e.g. Häggström and Lindroos 2016). Harvester size has been shown to effect productivity in the studied geographical region (e.g. Eriksson and Lindroos 2014). However, harvester size’s effect on productivity was not evaluated, since the study’s harvester sizes had been allocated to stands with different mean stand stem sizes. Even if the harvester size evaluation had been possible, the rather small range of mean stand stem sizes in this study (0.07–0.54 $m^3$ in final felling) might have proven too narrow to allow for such effects.

A significant effect of stem size variation on harvester productivity in final fellings was found in this study’s stand-based modeling. The presence of the effect indicates that the relationship between harvester time consumption and stem size is also unlikely to be linear in tree-based models, since if it was, no such effect would be found in the stand-based modeling. The tree-based relationship might naturally be linear in some specific cases, and is most likely to manifest in a narrow interval of stem sizes. The results support, however, the error in assuming that the relationship is naturally linear, which is in line with the conclusions from Ackerman et al.’s study on the effects of using tree-based models on stands with various tree-size distributions (Ackerman et al. 2024). The relationship is actually much more likely to be non-linear, since stem size does not have any influence on some of the work elements that constitute the harvester’s work (crane and machine movements) (c.f. Spinelli and Magagnotti 2013). In fact, it would not be enough that work elements such as felling and processing are linearly influenced by stem size (despite the likely technical limitations with large stems). Work elements such as crane out, machine relocations and miscellaneous time would also have to be linearly stem size dependent. The time consumption per stem of such work elements is most often found to be independent of stem size in empirical studies and are normally treated as constants, irrespective of stem size. Hence, one logical shape of the total time consumption would be convex (as shown in Figure 1), where the work elements with constant time consumption cause non-linearity for small stem sizes, and technical limitations cause non-linearity for large stem sizes (e.g. Kärhä et al. 2004; Visser and Spinelli 2012). Naturally, also other non-linear relationships could be reasonable.

The results from the final felling supported the effect of stand stem size variation on harvester productivity, but no such effect was found for thinnings. The reasons for this cannot be determined in this study, but there are several plausible explanations. The number of thinning stands corresponded to less than a quarter of the number of final felling stands. Moreover, the thinning stands contained less stand stem size variation, since the mean CV level was 37% in final fellings and 30% in thinnings (Table 1). Insufficient quantity and range of data are, hence, plausible causes for not being able to identify the effect from the noise in this study. The lack of effect might also be attributable to work differences between final felling and thinning. In thinning, more time is needed to position the crane and the machine due to considerations for residual trees, whereas the felling and processing of small stems requires relatively little time. Thus, the stem size-dependent work is likely to be proportionally smaller in thinning, so the effect of the stand stem size variation might be smaller and therefore not noticeable in the data.

The dataset used for this study was large, both in volume and in number of machines and operators. The study covered all seasons. Hence, the results of harvester productivity can be considered both reliable and representative for the conditions studied (northern Sweden).

There was considerable variation in stand sizes used in this stand-based study (Table 2), similar to the common variation in stem sizes seen in tree-based studies. Unlike tree-based studies, the variation in sizes of the observational units in stand-based studies is sometimes suggested to influence their representability. This is somewhat surprising, since the biggest trees can easily be 10 times larger than the smallest trees in a tree-based study, without considering the observation of the smallest trees being less representative. When using the time consumption per observational unit (or its inverse, the productivity) there is no certainty as to when the observed value is more or less representative. The values vary due to many different reasons, and the variation between observed units does not depend on the size of the unit per se. Hence, in this study, the size variation has been addressed as in tree-level modeling, by having many observations and avoiding ill-representative observations.

The variation of DBH within stands was used as an indication of stand stem size variation in this study. It is well known that the correlation between DBH and stem size (i.e. volume) is high (e.g. Zianis et al. 2005; Muukkonen 2007), and DBH has been used instead of stem size in productivity models (e.g. Ackerman et al. 2022). Nevertheless, the DBH variation might not have perfectly corresponded to the stem size variation in the stands. Moreover, the correlation between DBH and volume differs somewhat between tree species (e.g. Zianis et al. 2005; Muukkonen 2007), and therefore the estimated variation of stem sizes for a specific stand might be somewhat influenced by the tree species composition. This influence was, however, estimated to be minor, but should naturally be considered in future and more detailed studies.

The CV was used to quantify the stand stem size variation in this study, but there are other possible metrics that could be used. The CV was used here as a continuous variable, but also categorical approaches could be used for a coarser adjustment to the effect of the stand stem size variation like in Ackerman et al. (2024). This would require different types of stand stem size variations to be quantified and grouped together, according to their effect on productivity. This could, for instance, result in models that can be used to predict productivity based on mean stem volume (such as at present), which would be adjusted according to some available levels based on the stand's stem size variation.

Besides warranting additional studies on the effect of stand stem size variation, there are also practical implementations of the findings related to production and use of productivity models. Assuming that the stand stem size variation effect will be confirmed and addressed also in the future creation of harvester productivity models, both tree-based and stand-based models will still be relevant, if produced and applied in an appropriate way. For tree-based models, it is not expected that the modeling will require modification. However, the way tree-based models are applied to predict productivities in stands should be reconsidered. The first step would be to quantify when the stand stem size variation substantially influences the productivity, and when it is only negligible compared to other influential factors (cf. Ackerman et al. 2024). The influence will be a combination of the shape of the relationship between time consumption and stem size, and the stem size variation in the stand.

When aiming to accommodate the effect of stand stem size variation, the most accurate prediction of harvester productivity from tree-based models will come from summing the estimated time consumption for every single stem in the stand (c.f. Ager 1967). When doing so, the time consumption per stem will be based on its stem size and a model for harvester time consumption as a function of stem size. The stem size variation will then be automatically captured, and the stand's mean stem volume, as such, will not be used for the prediction.

This need for new considerations when creating and applying productivity models might be surprising, since harvesters are well-established and well-studied machines. However, recent research on forwarders has highlighted similar needs also for the oldest of the two machines in conventional mechanized CTL operations, pointing out the potential of using detailed data within stands instead of data aggregated into mean values (Manner et al. 2013, 2020). The new types of high-precision data are, in fact, the reason for recent developments in well-established fields of forest operation research. With new data available and the risk of bias from using mean stand values as input as demonstrated here, it is time to question whether the current way of producing and using harvester productivity models can still be considered appropriate and sufficiently accurate.

## Conclusion

This study found that the stem size variation within stands significantly affected harvester productivity in stand-based modeling. This indicates that data on stand stem size variation should be considered when creating stand-based models, as well as when applying both stem-based and stand-based productivity models for predictive purposes.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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