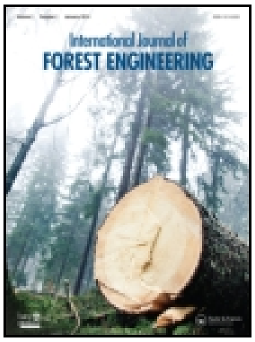


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# Productivity of harvesters and forwarders in CTL operations in northern Sweden based on large follow-up datasets

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Modern computerization facilitates data-gathering from forest machines, and offers new opportunities to develop models for predicting productivity in forest harvest operations. In this study, we analyze the productivity of cut-to-length harvesting and forwarding in thinning and final felling using a routinely recorded follow-up dataset. The data originate from over 700 machines that, over a 3-year period, harvested and forwarded more than 20 million $m^3$ of round-wood from upwards of 20 thousand stands, making the dataset larger than any that has previously been used for productivity modelling. Results comprise a range of stand-based productivity models of varying complexity for both harvesters and forwarders. Mean stem size was the most influential variable for harvesting productivity: modelling based on mean stem size explained 57.6% of the variance in thinnings and 55.3% in final fellings. However, accurate predictions of forwarding productivity required the simultaneous consideration of several variables. For instance, modelling of forwarder productivity based on the variables mean stem size, mean extraction distance and forwarder load capacity explained 26.4% of the variance in thinnings and 35.2% in final fellings. Results should be of interest to both practitioners and researchers interested in the study and modelling of forest operations.

**Keywords:** productivity; cut-to-length; harvester; forwarder; regression model

## Introduction

Planning, costing and control of forest operations are of major interest to the forestry industry. In order to deliver the demanded volumes of timber on time and at a competitive price, accurate predictions of the productivity of logging operations are required (Barnes 1937; Björheden 1991; Nieble & Freiwalds 2003). Thus, in the forestry industry, there is a long, ongoing tradition of developing and refining work productivity prediction models (e.g. Micklitz & Micklitz 1860; Tufts et al. 1988; Shrestha et al. 2005; Nurminen et al. 2006; Lindroos et al. 2010). Predictions are generally based on empirical data, but the amount of data used and the methodology used to acquire the information vary greatly, depending (*inter alia*) on the precision required and resources available. Commonly applied methods to assess performance in forestry include, for instance, time and motion studies (work observation), and follow-up studies (historical output records).

In time and motion studies, the productivity of a given observational unit is measured, normally over a rather short time. In contrast, follow-up studies rely on data gathered during normal production activities, using methodologies ranging from study-specific data collection to the use of existing records gathered as part of a company's normal follow-up routines. The use of follow-up studies has the major advantage of requiring few resources to compile data acquired over long periods. Further, it can provide more accurate information regarding normal performance than short-term studies, because effects of factors that only influence productivity occasionally (and thus would be missed in short-term studies, or heavily bias the results) can often be discerned. Moreover, ideally, the data-gathering should not interfere with normal work, i.e. there should be no observer effects. Notably, the well-known Hawthorne effect (i.e. the tendency for the performance of individuals to change when they are being

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studied, Mayo 1933; Vöry 1954) should be minimized. In addition, larger datasets are likely to cover a wider range of working conditions, machinery and operators, and thus are more likely to yield valid generalizations. It also allows forest companies to create and update their own predictive models, based on their own machine fleet and conditions, and as the accuracy of the automatic data-gathering and analyses increases, models based on the acquired data should become increasingly accurate and valuable (Palander et al. 2013). However, the level of detail and accuracy of routinely gathered datasets are generally lower than when researchers themselves gather data (cf. Purfürst & Lindroos 2011).

There is a vast array of models for predicting the productivity of cut-to-length (CTL) machinery in both thinning and final felling: see, for instance, Purfürst (2009) and Hiesl and Benjamin (2013) for reviews of harvester and forwarder productivity studies. However, even the predictive models that are intended to be representative of national forest operations are generally either based on a limited number of work samples and/or follow-up data because of the traditionally resource-hungry task of data-gathering. For instance, the model presented by Kuitto et al. (1994), which is considered to be quite comprehensive, was only based on data related to the productivity of operations in 132 stands in which ca. 11,000 m$^3$ of roundwood were harvested and forwarded by ca. 30 harvesters and forwarders. Since then, opportunities for data-gathering have improved considerably. The modern computerization of CTL machines makes it possible to automatically collect data using the machines' controller area network (CAN bus) and standards for production reports (StanForD (Anon 2010)). This computerization provides opportunities for gathering data that, previously, would have been difficult to acquire (e.g. Gerasimov et al. 2012; Palander et al. 2013; Strandgard et al. 2013). Heinimann (2001) modelled harvester productivity in final felling and thinning based on follow-up data from 2200 stands in western Germany; and Gerasimov et al. (2012) modelled productivity in Northwest Russia based on data from 38 harvesters that clearcut 1.4 million m$^3$ of roundwood. Purfürst (2009) modelled the productivity of medium-sized harvesters thinning pine-dominated stands, based on data from 32 operators working in 3500 stands in eastern Germany. Further, follow-up data has recently been used to model machine utilization, fuel consumption, and costs for harvesting operations (Holzleitner et al. 2011). Several issues were highlighted in the studies by Heinimann (2001) and Purfürst (2009), notably inconsistencies in the data between machines and uncertainties about the accuracy of the information.

Despite the rapid development of computerized data-gathering, these techniques still require some work before the data can be refined into usable databases. However, the benefits of keeping production databases for internal uses have been understood by some companies for a long time. For instance, since the late 1980s, the Swedish integrated forest company SCA Forest Products has collected and maintained an extensive database of the outcome of all their harvesting operations, in which ca. 7 million m$^3$ is harvested annually (i.e. almost 10% of the Swedish annual harvest) in the northern half of Sweden. Data collection started initially using the Swedish Mobitex system, and has now been developed such that data transfers from forest machines to the company's database are based on modern broadband technology. Some data are nowadays automatically collected and transferred, whereas other data are manually entered at some step in the data collection. Modern developments may further improve data collection, but the database maintained by SCA is already very attractive to developers of productivity models: its large size means that it constitutes a truly representative sample of productivity variation due to, for instance, forest and operator variations. To the best of our knowledge, such representative data has hitherto never been used for constructing productivity models. Therefore, the objective of this study was to develop models for predicting harvester and forwarder productivity in CTL thinning and final felling operations, based on a dataset containing information related to the activities of more than 700 machines handling ca. 20 million m$^3$ of roundwood in more than 20,000 stands. In this work, we also discuss some of the challenges related to productivity modelling when using this large dataset.

## Material and methods

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.

### *Historical output data*

Output data were collected from records of normal work between January 2009 and April 2012 by the Swedish forestry company SCA, following the company's normal follow-up routines. SCA's operations are performed in managed forests dominated by

Scots pine (*Pinus sylvestris*) and Norway spruce (*Picea abies*), located between approximate latitudes 62° and 66° in Sweden. Forests that were subject to several selection cuttings until the mid-twentieth century are now normally being subjected to final fellings, while first thinnings are generally being applied in homogenous forests planted during the second half of the twentieth century. Final fellings are normally done as clearcuts, with or without seed trees left for later recovery. Thinnings include some stands dominated by a third coniferous species, lodgepole pine (*Pinus contorta*), which was widely introduced in northern Sweden during the 1970s. In thinning, the company did not apply the common strip road methodology (in which both harvesters and forwarders travel along strip roads located at 20 m intervals in the stands). Instead, thinning was carried out with so-called intermediate harvester passages (also known as cutting strips or ghost trails) between strip roads spaced 25–30 m apart. Typically, this thinning method results in harvest of approximately 30–40% of the basal area. Since the forwarders only travel along strip roads, the harvesters place logs by those roads when thinning the intermediate passages. The methodology has been further explained and evaluated by several authors, e.g. Kärhä et al. (2004). Harvest operations were carried out in compliance with legal requirements and the company's environmental standards, but without detailed standards for the felling and forwarding work. The harvesters typically used during the study period included the Valmet/Komatsu 901 and John Deere (JD) 1070 for thinning and the Valmet 911 and John Deere 1270 for final felling, while the forwarders typically used were the Valmet 860 and John Deere 1410 for thinning and Valmet 890 and John Deere 1710 for final felling. However, these machines were not exclusively used in either thinning or final felling; various other brands and sizes of machines were also frequently used in the operations studied.

Data were extracted from SCA's IT systems and compiled into four separate datasets, describing the work of both harvesters and forwarders in thinnings and final fellings. In total, 36 variables were used in the analysis (Table 1), of which some were combined in the analysis to evaluate possible interaction effects. Most of the variables were in their original reported form, whereas some data in the database were derived from reported data. Such derived data were, for instance, productivity (solid $m^3$ of roundwood under bark per productive, delay-free machine hour ($m^3$/PMh), derived from the total harvested volume on a site divided by the corresponding sum of productive machine hours for the studied machine on the site), mean stem size ($m^3$, derived from the total harvested volume on a site divided by the corresponding sum of harvested trees), and harvest per hectare (stems/ha and $m^3$/ha, derived from the sum of harvested trees, respectively the total harvested volume, divided by the harvested area for each stand). All volumes were measured by independent wood measuring organizations, normally after the wood was transported to industries or terminals. Terrain roughness and slope were measured according to Berg (1992) for a number of plots in each stand, and recorded in the dataset as the mean value of these plots for each stand. Some of the variables were binomial; for instance, either the stand contained predominantly lodgepole pine (value = 1) or it did not (i.e. it contained predominantly other tree species, value = 0) and either the stand was harvested in a manner adapted for subsequent recovery of logging residues (LR) or it was not. Two dummy variables, taking the binomial value 1 if relevant and 0 otherwise, were also created to indicate the cutting of seed trees (after the establishment of natural regeneration, mainly of Scots pine) and abnormal operations e.g. removal of trees before building roads. Based on harvesting dates, dummy variables were created to indicate snow obstruction (for operations starting in January – March) and limited daylight (for operations starting in October – February).

Dummy variables were also created to evaluate the effects of the size of the harvester base machine and of the harvester head. Harvester base machine sizes were subjectively classified, where small (S) was considered to be the size of e.g. JD 770, medium (M) the size of e.g. JD 1070, large (L) the size of e.g. JD1170, extra-large (XL) the size of e.g. JD 1270, extra-extra-large (XXL) the size of e.g. JD 1470 and extra-extra-extra-large (XXXL) the size of e.g. Komatsu 941. Similarly, harvester heads were subjectively classified, where small (S) was considered to be the size of e.g. Valmet 330, medium (M) the size of e.g.Valmet 340, large (L) the size of e.g. Valmet 350, extra-large (XL) the size of e.g. Valmet 365 and extra-extra-large (XXL) the size of e.g. Valmet 370. Data on the harvester heads' mass and cutting diameter were collected from the manufacturers' technical information; information about the accumulating capacity of the harvesting heads (binary, 1 = yes) were collected from SCA's records of each machine's configuration and equipment. Not all the machine sizes are equipped with the full range of harvester heads since, for instance, a small machine will have difficulties in handling a heavy head due to a too weak construction, insufficient crane torque, and insufficient machine mass acting as a counterweight. Thus, larger machines were

Table 1. Stand and machine variables that were tested as independent variables for the productivity models, with characteristics presented for the outlier-reduced dataset.

| Variable | Unit/Class | Final felling Mean | Final felling SD | Final felling Min–max | Final felling 10th-90th perc. | Thinning Mean | Thinning SD | Thinning Min–max | Thinning 10th–90th perc. | Data capture[a] |
|---|---|---|---|---|---|---|---|---|---|---|
| *Applied to both harvesting and forwarding modelling* | | | | | | | | | | |
| 1. Mean stem size | $m^3$ | 0.25 | 0.14 | 0.05–1.82 | 0.11–0.42 | 0.11 | 0.05 | 0.03–0.48 | 0.06–0.16 | A |
| 2. Harvested volume per ha | $m^3$/ha | 165 | 80 | 2–714 | 64–267 | 48 | 19 | 5–335 | 31–67 | M/A[b] |
| 3. Total harvested volume | $m^3$ | 1357 | 1637 | 1–22468 | 141–3210 | 624 | 666 | 6–10700 | 102–1435 | A |
| 4. Terrain roughness | 1-5 | 1.8 | 0.6 | 1.0–5.0 | 1.0–2.6 | 1.7 | 0.5 | 1.0–5.0 | 1.0–2.4 | M |
| 5. Slope | 1-5 | 1.7 | 0.6 | 1.0–5.0 | 1.0–2.5 | 1.6 | 0.5 | 1.0–4.0 | 1.0–2.4 | M |
| 6. Bucked assortments | n | 3.5 | 0.7 | 1–7 | 3–4 | 3.1 | 0.8 | 1–6 | 2–4 | M |
| 7. NIPF-owned[c] | 0/1 | 0.52 | – | 0–1 | 0–1 | 0.46 | – | 0–1 | 0–1 | M |
| 8. Expected daylight limitation | 0/1 | 0.32 | – | 0–1 | 0–1 | 0.28 | – | 0–1 | 0–1 | A |
| 9. Expected snow limitations | 0/1 | 0.29 | – | 0–1 | 0–1 | 0.27 | – | 0–1 | 0–1 | A |
| 10. LR[d] recovery adaption | 0/1 | 0.11 | – | 0–1 | 0–1 | – | – | – | – | M |
| 11. Seed tree harvest | 0/1 | 0.05 | – | 0–1 | 0–0 | – | – | – | – | M |
| 12. Abnormal operation | 0/1 | 0.13 | – | 0–1 | 0–1 | – | – | – | – | M |
| 13. Lodgepole pine stand | 0/1 | – | – | – | – | 0.13 | – | 0–1 | 0–1 | M |
| *Applied only to the modelling of harvesting* | | | | | | | | | | |
| 14. Harvested trees | trees/ha | 754 | 342 | 50–2000 | 309–1188 | 493 | 198 | 50–1845 | 285–730 | A |
| 15. Undergrowth | trees/ha | 515 | 675 | 0–7000 | 0–1201 | 602 | 790 | 0–10000 | 0–1500 | M |
| 16. Difficult trees | % + 1 | 3.02 | 5.15 | 1–101 | 1–6 | 4.14 | 6.25 | 1–62 | 1–11 | M |
| Machine size | | | | | | | | | | |
| 17. S | 0/1 | <0.01 | – | 0–1 | 0–0 | 0.02 | – | 0–1 | 0–0 | M |
| 18. M | 0/1 | 0.23 | – | 0–1 | 0–1 | 0.68 | – | 0–1 | 0–1 | M |
| 19. L | 0/1 | 0.11 | – | 0–1 | 0–1 | 0.13 | – | 0–1 | 0–1 | M |
| 20. XL | 0/1 | 0.39 | – | 0–1 | 0–1 | 0.16 | – | 0–1 | 0–1 | M |
| 21. XXL | 0/1 | 0.16 | – | 0–1 | 0–1 | <0.01 | – | 0–1 | 0–0 | M |
| 22. XXXL | 0/1 | 0.09 | – | 0–1 | 0–0 | <0.01 | – | 0–1 | 0–0 | M |
| Harvester head size | | | | | | | | | | |
| 23. S | 0/1 | 0.03 | – | 0–1 | 0–0 | 0.11 | – | 0–1 | 0–1 | M |
| 24. M | 0/1 | 0.20 | – | 0–1 | 0–1 | 0.48 | – | 0–1 | 0–1 | M |
| 25. L | 0/1 | 0.28 | – | 0–1 | 0–1 | 0.38 | – | 0–1 | 0–1 | M |
| 26. XL | 0/1 | 0.18 | – | 0–1 | 0–1 | 0.02 | – | 0–1 | 0–0 | M |
| 27. XXL | 0/1 | 0.31 | – | 0–1 | 0–1 | 0.01 | – | 0–1 | 0–0 | M |
| 28. Mass | kg | 1025 | 310 | 480–1681 | 760–1300 | 862 | 120 | 480–1470 | 670–960 | M |
| 39. Cutting diameter | cm | 62 | 16 | 45–90 | 53–71 | 59 | 5.3 | 45–82 | 50–64 | M |
| 30. Stem accumulation | 0/1 | 0.21 | – | 0–1 | 0–1 | 0.28 | – | 0–1 | 0–1 | M |
| *Applied only to the modelling of forwarding* | | | | | | | | | | |
| 31. Mean extraction distance (MFD) | m | 424 | 292 | 50–3000 | 140–800 | 422 | 275 | 50–2500 | 150–800 | M[e] |
| 32. Forwarder load capacity | $m^3$ | 16.4 | 2.4 | 5–22 | 14–19 | 11.9 | 9.7 | 6–21 | 11–14 | M |
| 33. Adjustable load space | 0/1 | 0.48 | – | 0–1 | 0–1 | 0.33 | – | 0–1 | 0–1 | M |
| 34. Assortments at landing[f] | n | 4.9 | 1.2 | 1–10 | 4–6 | 4.1 | 1.1 | 1–8 | 3–5 | M |

SD = standard deviation. [a]*A* = automatic recording and data entry; *M* = manual assessment and data entry. [b]Volume automatically recorded and entered, but area manually assessed and entered. [c] Whether or not the stand was owned by SCA or by a non-industrial private forest (NIPF) owner. [d]Logging residue. [e]Mean one-way extraction distance assessed prior to the harvest. The actual extraction distances were not recorded in the follow-up system. [f]All assortments, irrespective of volume. Assortments at landing are normally more than Assortments bucked, due to, for instance, the separation of logs that do not meet quality requirements. (e.g. due to root rot).
Note: dummy variables are given the value 1 if the stand conditions match the statement (e.g. if owned by a NIPF owner) and 0 otherwise (e.g. if owned by SCA). Mean values indicate the proportional occurrence of each variable (e.g. 52% of stands in finnal fellings were owned by NIPF owners).

Table 2. Average harvester head (HH) mass and cutting diameter for each harvester size.

| | Final felling | | Thinning | |
|---|---|---|---|---|
| Harvester class | HH mass (kg) | HH cutting diam (cm) | HH mass (kg) | HH cutting diam (cm) |
| S | 699 | 48 | 684 | 47 |
| M | 826 | 57 | 840 | 58 |
| L | 898 | 60 | 880 | 60 |
| XL | 1051 | 63 | 941 | 61 |
| XXL | 1177 | 68 | 1232 | 70 |
| XXXL | 1401 | 67 | 1470 | 70 |

Note: averages were calculated over stands in which harvesters of a given size had been working. Some classes were rarely used in final felling whereas others were rarely used in thinning (cf. Table 1).

Table 3. Numbers of stands by cutting type and numbers of machines used in them.

| | Harvesters | | Forwarders | |
|---|---|---|---|---|
| | Final felling | Thinning | Final felling | Thinning |
| Total stand number (*N*) | 14782 | 5597 | 14947 | 5548 |
| Stands with no missing data (*n*) | 13031 | 4956 | 13703 | 5264 |
| *After full outlier reduction* | | | | |
| Stands (*n*) | 12350 | 4851 | 12552 | 4907 |
| Total volume ($10^6$ m$^3$) | 17.1 | 3.05 | 17.2 | 3.09 |
| Machines (*n*[a]) | 423 | 270 | 341 | 229 |

Note: [a]the same machine may have been used in both final felling and thinning and thus data related to its operations may appear in both datasets.

generally equipped with larger and heavier harvester heads (Table 2). Moreover, some harvester and harvester head classes have rarely been used for final felling or for thinning (cf. Table 1).

Size effects for forwarders were considered to be taken into account by using the forwarders' theoretical load capacity. Load capacity refers to the expected average load size given a certain machine type's available load space, maximum load weight according to the manufacturer, and the normal length and weight of logs handled in normal operations. In the follow-up process, the company also calculated the average payload in each stand as the total harvested volume divided by the reported number of forwarded loads. However, neither number of loads nor average payload was used in the modelling due to the lack of such data prior to harvesting. Thus, its predictive capacity is limited. Further, the derived payload data was sensitive to the accuracy of both total volume and forwarded load data, and some problems were identified in the intervals recorded for these variables. The data showed a mean payload of 16.2 m$^3$ in final felling (median 15.8, interval 0–489) and 11.9 m$^3$ in thinning (median 11.3, interval 0–596). For forwarded loads per stand, the mean was 117 in final fellings (median 497, interval 1–18051) and 101 in thinnings (median 577, interval 1–19899).

The total dataset comprised data related to ca. 15,000 stands that were final felled and ca. 5,600 stands that were thinned (Table 3). However, the data were incomplete for almost 12% of the stand records, hence data for these stands were excluded. Moreover, the data for some stands that had no missing values contained obvious inaccuracies, as shown in Figure 1. For instance, more than 1% of the final felling stands were recorded with mean stem volumes of zero m$^3$. Further examples of

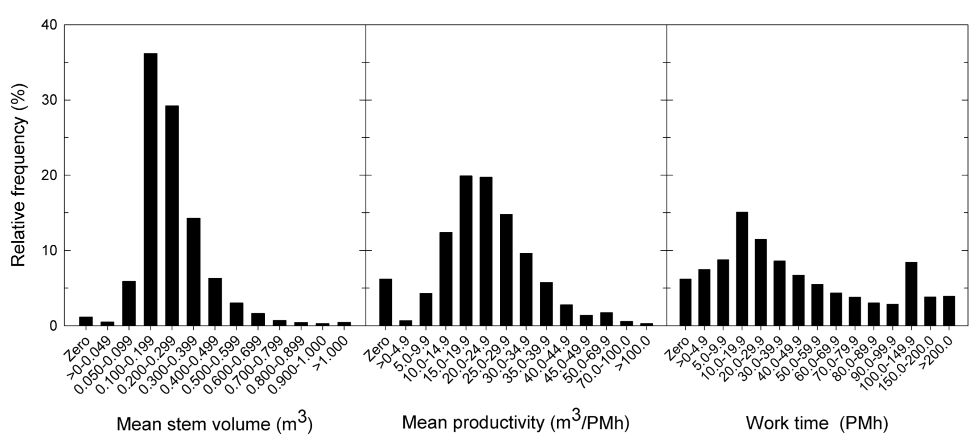


Figure 1. Relative frequency distributions of stands with respect to mean stem volume (left), mean productivity (centre) and work time (right) in the full dataset for harvesters in final fellings (*N* = 14 782 stands).

obvious inaccuracies are the proportions of zero work time and hence zero productivity (6% of the stands). This prompted the development of a simple algorithm for reducing frequencies of outliers based, from experience, on reasonable values. The outlier reduction algorithm was designed to remove obvious errors from the data while tolerating cases that could potentially be erroneous but might be unusual observations that had been correctly recorded. Stands were considered as outliers if the associated data did not comply with all of the following conditions:

- Work time of >1 PMh
- Reported productivity was between 30% and 200% of the company's general expected productivity (expected value = 100%).
- Mean stem size was 0.03–0.50 $m^3$ in thinning and 0.05–2.00 $m^3$ in final felling.
- Mean extraction single trip distances were ≥10 m and <3000 m.
- Harvested volume per hectare was >0 $m^3$/ha.
- Slope or ground roughness class was ≥1 and ≤5.
- Between 50 and 2000 trees/ha were removed.

When the outlier reduction algorithm was applied to the data, an additional 7% of the stands were removed from the analysis, resulting in the retention of data for more than 12,000 final felling stands and almost 5000 thinning stands (Table 3). The data from those stands originated from recordings from more than 420 harvesters and 340 forwarders used in final felling and ca. 270 harvesters and 230 forwarders used in thinning (Table 3). Many of these machines were used for both thinning and final felling and thus appear in both the final felling and thinning datasets.

The data collected from the machines' computers also included information on the distribution of productive machine hours (PMh) and delays registered by the machine computers. In these data, computer-registered work time was classified into five classes: productive machine time, repairs, maintenance, relocations and other delays (Table 4). For events during which the machines' systems are deactivated, such as some workplace meetings, work planning sessions and major breakdowns, manual registration is required by the operator to obtain accurate records of all scheduled work hours. However, based on experience, this is not always correctly done, which means that some delays have, most likely, been unaccounted for here.

Table 4. Proportions (%) of total machine computer uptime of productive machine time (PMh) and classes of delay times.

| | Harvesters | | Forwarders | |
|---|---|---|---|---|
| Machine time | Final felling | Thinning | Final felling | Thinning |
| Productive machine time | 78.3 | 79.1 | 83.8 | 84.1 |
| Delays | | | | |
| Repairs | 5.9 | 5.9 | 3.7 | 3.1 |
| Maintenance | 6.3 | 5.9 | 4.9 | 4.6 |
| Relocation | 1.5 | 1.4 | 0.9 | 1.1 |
| Other delays | 7.8 | 7.8 | 6.7 | 7.2 |

### *Statistical analysis*

Models for predicting machine productivity were developed using linear regression based on ordinary least squares (OLS) parameter estimation. The analytical process comprised the following steps:

(1) Visual and statistical analysis of correlations between independent variables and their correlations with machine productivity.
(2) Estimation of parameters and analysis of significance by OLS regression analysis.
(3) Analysis of the models' standardized residuals so they do not violate the assumptions of linearity, independence, homoscedasticity and normality of errors. Monitoring of the variance inflation factor to avoid problems due to possible multicolinearity.
(4) Adjustment of the model (e.g. inclusion/exclusion of and/or transformation of variables).
(5) Repetition of steps 2–4 until the model was satisfactory and all model assumptions were met.

Productivity models are likely to be applied in diverse practical situations, in which varying degrees of input variables are available. Therefore, models with varying degrees of complexity were developed. The simplest models include variables that are well known to influence machine work productivity (model categories *i* and *ii*) and other models (*iii* and *iv*) were based on a combination of a priori knowledge and examination of the data. However, a challenge with this kind of extensive data is that most of the available variables significantly contributed to the models. Thus, the knowledge-based analyses were complemented with an automated procedure of model selection to further examine the data. The method used was bi-directional stepwise regression analysis, in which the variable that meets given inclusion and exclusion criteria and explains most of the variation is entered first into the model. Then, other qualified variables are entered and excluded stepwise according to their contribution to the level of explained variation. The procedure stops when there is no model change available that meets the inclusion or exclusion criteria of variables. Inclusion and exclusion criteria were both set to $\alpha = 0.15$, which means that a variable was entered if its $p$-value for the given model was <0.15 and removed from a given model if its $p$-value was >0.15.

In order to meet the assumptions of linear regression, most data included in the study were transformed to their natural logarithms (Ln) during the analyses. As the dependent variables were transformed, results from the models developed need 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 & Tang 2011). All analyses were carried out using Minitab 16 (Mintab Inc., USA) with the critical significance level set to 5% (besides in the stepwise regressions).

## Results

The results are described with harvester productivity models for final felling and thinning, respectively, being presented first, followed by a similar order for forwarder work. Since the outputs from the stepwise regression analyses are extensive, they are summarized in this section. Full tables are presented in the Appendix. The last section of the results briefly addresses the conversion of the model's productive work time into scheduled work time.

### ***Harvester productivity***

#### *Final felling*

The mean of harvester productivity in final felling was 23.8 $m^3$/PMh (SD 10.1, median 22.3, range 0.9–122.1). As expected, the mean stem size explained most of the observed variance ($R^2$-adj >53%) in final felling (models *i* in Table 5). Productivity increased with mean stem size and/or its square product, and the productivity increase declined (curve linearly) with increases in mean tree sizes (Figure 2). Productivity also increased with increases in total harvested volume per stand and harvested volume per hectare (model *ii*), with the former being more influential than harvested volume per hectare in both final felling and in thinning.

In model *iii*, further variables related to the stand characteristics have been added, and in models *iv* and *v*, variables relating to harvester head and machine size have been added. However, the classification groups of harvester head sizes did not contribute to the models. In general, many variables contributed significantly to the model, but there were only marginal improvements in terms of the explained level of observed variation between model *i* with only one variable ($R^2$-adj = 55.3%) and model *v* with 17 variables ($R^2$-adj = 62.6%) (Table 5). Similarly, in the truly exploratory stepwise regression analysis, 24 of 29 entered variables significantly contributed but with only marginal model improvements ($R^2$-adj = 63.8%, Appendix 1). The only variables that did not contribute were variable 14, and interactions between variable 1 and variables 18, 20, 24 and 26 (see Table 1 for variable names). In the stepwise regression, most of the variables in model *v* were included, except the interaction between variables 1 and 18, and 1 and 20.

Although the influence on productivity of other contributing variables was generally quite modest in comparison to the mean tree size, the analyses indicate that productivity decreased with higher numbers of difficult trees, difficult terrain conditions, increasing amounts of understory, number of bucked assortments, expected snow limitations, felling of seed-trees, abnormal operations, and on forest land owned by non-industrial private forest (NIPF) owners.

In contrast, productivity in final felling was positively influenced by the total volume harvested and the harvested volume per hectare, use of an accumulating harvester head, the harvester head's mass and, surprisingly, expected daylight limitations. The machine size's effect varied depending on the mean stem size, with larger machines generally being more productive at all mean stem sizes (Figure 3). However, the difference was largest in the middle of the data range, with less difference for both small and larger stem sizes. There were only very small differences in productivity between machine sizes M and L as well as between XL and XXL. In fact, those size groups were, in practice, pooled in the stepwise regression.

#### *Thinning*

The mean of harvester productivity in thinning was 11.3 $m^3$/PMh (SD 4.9, median 10.3, range 0.1–

Table 5. Harvester productivity models ($n$ = 12350 and 4851 for harvester operations in final felling and thinning, respectively).

| Operation | Model category | Variable | Parameter estimate | SE | $p$-value | $R^2$-adj (%) | RMSE |
|---|---|---|---|---|---|---|---|
| Final felling | *i* | Full model | – | – | <0.001 | 55.3 | 0.29 |
| | | Intercept | 3.704 | 0.016 | <0.001 | | |
| | | Ln(Mean stem size) | 0.134 | 0.022 | <0.001 | | |
| | | (Ln(Mean stem size))$^2$ | −0.161 | 0.007 | <0.001 | | |
| | *ii* | Full model | – | – | <0.001 | 60.0 | 0.27 |
| | | Intercept | 3.135 | 0.023 | <0.001 | | |
| | | Ln(Mean stem size) | 0.378 | 0.022 | <0.001 | | |
| | | Ln(Total harvested volume) | 0.066 | 0.002 | <0.001 | | |
| | | Ln(Harvested volume per ha) | 0.056 | 0.004 | <0.001 | | |
| | | (Ln(Mean stem size))$^2$ | −0.072 | 0.007 | <0.001 | | |
| | *iii* | Full model | – | – | <0.001 | 61.7 | 0.27 |
| | | Intercept | 3.148 | 0.023 | <0.001 | | |
| | | Ln(Mean stem size) | 0.379 | 0.021 | <0.001 | | |
| | | Ln(Total harvested volume) | 0.077 | 0.002 | <0.001 | | |
| | | Ln(Harvested volume per ha) | 0.060 | 0.004 | <0.001 | | |
| | | (Ln(Mean stem size))$^2$ | −0.071 | 0.007 | <0.001 | | |
| | | Ln(Terrain roughness × Slope) | −0.079 | 0.004 | <0.001 | | |
| | | Ln(Difficult trees) | −0.038 | 0.003 | <0.001 | | |
| | | LR recovery adaptation | −0.044 | 0.008 | <0.001 | | |
| | *iv* | Full model | – | – | <0.001 | 62.5 | 0.26 |
| | | Intercept | 2.371 | 0.095 | <0.001 | | |
| | | Ln(Mean stem size) | 0.365 | 0.021 | <0.001 | | |
| | | Ln(Total harvested volume) | 0.075 | 0.002 | <0.001 | | |
| | | Ln(Harvested volume per ha) | 0.061 | 0.004 | <0.001 | | |
| | | (Ln(Mean stem size))$^2$ | −0.072 | 0.007 | <0.001 | | |
| | | Ln(Terrain roughness × Slope) | −0.076 | 0.004 | <0.001 | | |
| | | Ln(Difficult trees) | −0.033 | 0.003 | <0.001 | | |
| | | LR recovery adaptation | −0.042 | 0.008 | <0.001 | | |
| | | Expected daylight limitation | 0.026 | 0.006 | <0.001 | | |
| | | Expected snow limitation | −0.031 | 0.006 | <0.001 | | |
| | | Ln(Undergrowth) | −0.004 | 0.001 | <0.001 | | |
| | | Accumulating harvesting head | 0.073 | 0.006 | <0.001 | | |
| | | Ln(Harvesting head weight) | 0.109 | 0.013 | <0.001 | | |
| | *v*[a] | Full model | – | – | <0.001 | 62.6 | 0.26 |
| | | Intercept | 2.704 | 0.141 | <0.001 | | |
| | | Ln(Mean stem size) | 0.353 | 0.022 | <0.001 | | |
| | | Ln(Total harvested volume) | 0.075 | 0.002 | <0.001 | | |
| | | Ln(Harvested volume per ha) | 0.062 | 0.004 | <0.001 | | |
| | | (Ln(Mean stem size))$^2$ | −0.067 | 0.007 | <0.001 | | |
| | | Ln(Terrain roughness × Slope) | −0.077 | 0.004 | <0.001 | | |
| | | Ln(Difficult trees) | −0.034 | 0.003 | <0.001 | | |
| | | LR recovery adaptation | −0.042 | 0.008 | <0.001 | | |
| | | Expected daylight limitation | 0.027 | 0.006 | <0.001 | | |
| | | Expected snow limitation | −0.032 | 0.006 | <0.001 | | |
| | | Ln(Undergrowth) | −0.004 | 0.001 | <0.001 | | |
| | | Accumulating harvesting head | 0.079 | 0.006 | <0.001 | | |
| | | Ln(Harvesting head weight) | 0.061 | 0.020 | 0.002 | | |
| | | HS S × Ln(Mean stem size) | 0.112 | 0.020 | <0.001 | | |
| | | HS M × Ln(Mean stem size) | 0.027 | 0.010 | 0.003 | | |
| | | HS L × Ln(Mean stem size) | 0.039 | 0.010 | <0.001 | | |
| | | HS XL × Ln(Mean stem size) | 0.024 | 0.008 | 0.002 | | |
| | | HS XXL × Ln(Mean stem size) | 0.022 | 0.008 | 0.004 | | |
| Thinning | *i* | Full model | – | – | <0.001 | 57.6 | 0.25 |
| | | Intercept | 3.466 | 0.069 | <0.001 | | |
| | | Ln(Mean stem size) | 0.211 | 0.063 | 0.001 | | |
| | | (Ln(Mean stem size))$^2$ | −0.112 | 0.014 | <0.001 | | |

(*continued*)

Table 5. (*Continued*).

| Operation | Model category | Variable | Parameter estimate | SE | *p*-value | $R^2$-adj (%) | RMSE |
|---|---|---|---|---|---|---|---|
| | *ii* | Full model | – | – | <0.001 | 58.1 | 0.25 |
| | | Intercept | 3.592 | 0.058 | <0.001 | | |
| | | Ln(Mean stem size) | 0.693 | 0.009 | <0.001 | | |
| | | Ln(Total harvested volume) | 0.037 | 0.004 | <0.001 | | |
| | | Ln(Harvested volume per ha) | 0.039 | 0.011 | <0.001 | | |
| | *iii* | Full model | – | – | <0.001 | 59.8 | 0.25 |
| | | Intercept | 3.514 | 0.058 | <0.001 | | |
| | | Ln(Mean stem size) | 0.665 | 0.009 | <0.001 | | |
| | | Ln(Total harvested volume) | 0.051 | 0.004 | <0.001 | | |
| | | Ln(Harvested volume per ha) | 0.047 | 0.011 | <0.001 | | |
| | | Ln(Terrain roughness × Slope) | −0.037 | 0.007 | <0.001 | | |
| | | Ln(Difficult trees) | −0.035 | 0.004 | <0.001 | | |
| | | Ln(Undergrowth) | −0.008 | 0.001 | <0.001 | | |
| | *iv*[b] | Full model | – | – | <0.001 | 61.2 | 0.24 |
| | | Intercept | 2.822 | 0.203 | <0.001 | | |
| | | Ln(Mean stem size) | 0.638 | 0.010 | <0.001 | | |
| | | Ln(Total harvested volume) | 0.051 | 0.004 | <0.001 | | |
| | | Ln(Harvested volume per ha) | 0.057 | 0.011 | <0.001 | | |
| | | Ln(Terrain roughness × Slope) | −0.039 | 0.007 | <0.001 | | |
| | | Ln(Difficult trees) | −0.033 | 0.004 | <0.001 | | |
| | | Ln(Undergrowth) | −0.007 | 0.001 | <0.001 | | |
| | | Expected daylight limitation | 0.021 | 0.009 | 0.016 | | |
| | | Expected snow limitation | −0.045 | 0.009 | <0.001 | | |
| | | Accumulating harvesting head | 0.051 | 0.009 | <0.001 | | |
| | | Ln(Harvesting head weight) | 0.281 | 0.037 | <0.001 | | |
| | | Ln(Max cutting diameter) | −0.314 | 0.055 | <0.001 | | |
| | | HS S × Ln(Mean stem size) | 0.041 | 0.012 | <0.001 | | |
| | | HS M × Ln(Mean stem size) | 0.020 | 0.004 | <0.001 | | |
| | | HS L × Ln(Mean stem size) | 0.018 | 0.006 | 0.002 | | |

[a]setting all dummy variables with harvester size (HS) equal to 0 results in the productivity for harvester size XXXL. [b]setting all dummy variables with HS equal to 0 results in the productivity for a pooled value for harvesters with **sizes** larger than L.
Note: models are for Ln(y), where *y* = productivity in $m^3$/PMh. The coefficient (intercept) is not corrected for logarithmic bias, and should thus be increased by $RMSE^2/2$ when estimating y (see section 3.3).

62.1). As for final felling, the mean stem size explained most of the observed variance ($R^2$-adj >57%) in thinning (model *i* in Table 5), and the productivity increase declined (curve linearly) with increases in mean tree sizes (Figure 2).

Many additional variables contributed significantly to the model, but there were only marginal improvements in terms of the explained level of observed variation between model *i* with only one variable ($R^2$-adj = 57.6%) and model *iv* with 14 variables ($R^2$-adj = 61.2%) (Table 5). Similarly, in the truly exploratory stepwise regression analysis, 22 out of 27 variables significantly contributed but with only marginal model improvements ($R^2$-adj = 63.1%, Appendix 2). The only variables that did not contribute were the interaction between variable 1 and variables 18, 19, 23, 25, and 27. In the stepwise regression, most of the variables in model *iv* were included, apart from the interaction between variables 1 and18, and 1 and 19.

In thinning, the influence of the various variables was similar to that in final felling. The only additional effects were that thinning productivity decreased with harvester head cutting diameter, and that the effect of machine size was limited. Productivity was significantly higher with larger machines sizes (model *iv*, Table 5), but the differences were small for actual productivity values (Figure 2). The productivity of the pooled machine sizes >L was quite close to the S group's productivity in final felling.

### *Forwarder productivity*

#### *Final felling*

The mean productivity of the forwarding work in final felling was 21.4 $m^3$/PMh (SD 7.56 median 20.7, range 0.01–122.0). Compared to harvesting, more variables were needed to explain enough observed variation to justify use of the models for

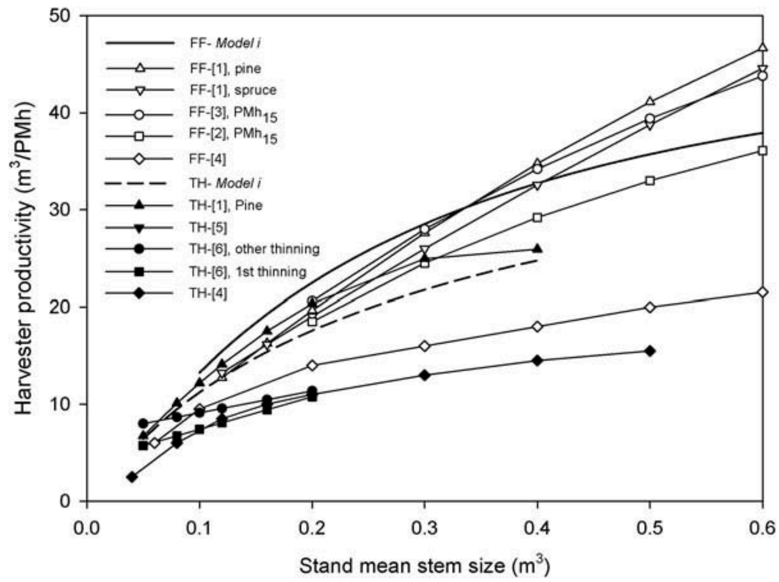


Figure 2. Harvesting productivity in final felling (FF) and thinning (TH) as predicted by the models category *i* (corrected for Ln-bias), together with predictions obtained from models reported in the following previous publications: [1] Nurminen et al. (2006), [2] Brunberg (1995), [3] Brunberg (2007), [4] Kuitto et al. (1994), [5] Purfürst (2009) and [6] Sirén and Aaltio (2003).

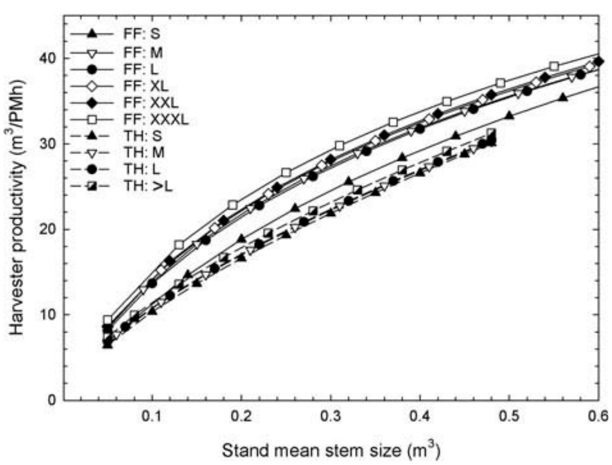


Figure 3. Harvester productivity over machine sizes and mean stem size, based on model *v* for final felling and model *iv* for thinning. FF = final felling, and TH = thinning. Mean values from Tables 1 and 2 have been used for variables other than mean stem size and machine size.

predictions. The variable that explained most of the variation was the Ln-transformed square product of the mean extraction distance ($R^2$-adj = 16.6%, Appendix 3). By adding the Ln-transformed product of load capacity and mean extraction distance, almost twice as much of the variation could be explained ($R^2$-adj = 29.8%, data not shown). Thus, in the first level model (*i*), the variables mean extraction distance, the interaction between load capacity and mean extraction distance, and mean stem size were combined, and explained slightly more than one third of the observed variation ($R^2$-adj = 35.2%) in final felling (Table 5, Figure 4). Adding the binomial variable denoting whether or not a forwarder was equipped with an adjustable load space had little effect on model performance (model *ii*, $R^2$-adj = 35.6%). In model *iii*, variables for stand conditions were also added to the model (total stand volume, harvested volume per hectare,

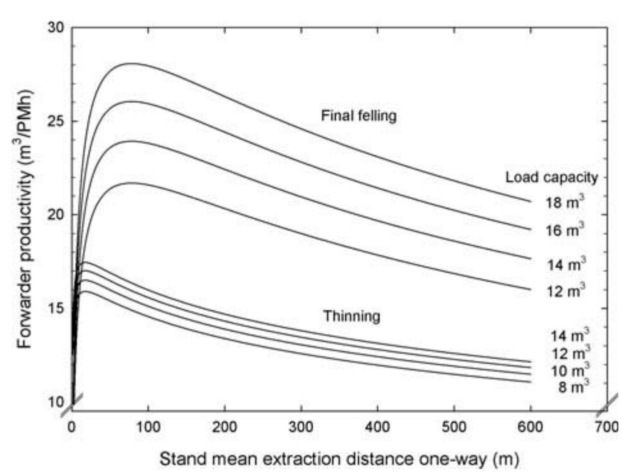


Figure 4. Predicted effects of load size on forwarding productivity in final felling and thinning as a function of distance according to models in category *i*. Mean stem size was set to 0.25 $m^3$ in final felling and 0.11 $m^3$ in thinning.

and terrain conditions), which increased its $R^2$-adj by almost 10 percentage points ($R^2$-adj 43.4%). Adding information on the number of assortments at landing had little effect on model performance (model *iv*, $R^2$-adj = 43.9%).

Similarly, in the truly exploratory stepwise regression analysis, 15 out of 17 entered variables significantly contributed, but did not increase the level of explained variance to more than 44.3% (Appendix 3). The only variables that did not contribute were 6 and 31. In the stepwise regression, the variables in model *iii* were also included.

The analyses indicate that forwarder productivity decreased with higher mean extraction distance, difficult terrain conditions, number of assortments at landing, at LR-recovery adapted fellings, expected daylight limitations, on forest land owned by non-industrial private forest (NIPF) owners and in abnormal operations. Productivity in final felling was increased by load capacity, the total volume harvested, harvested volume per hectare, mean stem size, expected snow limitations, seed-tree harvest and use of adjustable load space.

Forwarders with high load capacity had higher productivity at all extraction distances (Figure 4), and the effect varied depending on the mean extraction distance (Table 6). However, the differences in absolute values were relatively consistent over distance, resulting in larger relative differences at longer distances (Figure 4).

### *Thinning*

The mean productivity of the forwarding work in the thinning operations was 12.9 $m^3$/PMh (SD 4.5, median 12.2, range 0.2–100.0). Compared to the other modeling, forwarder work in thinning proved to be the most difficult to model. In fact, the created models (*i* – *iii*) explained at best only one third of the observed variation (Table 6). In the truly exploratory stepwise regression analysis, the mean stem size turned out to be the single variable that explained most of the variation ($R^2$-adj = 15.5%, Appendix 4). By adding the square product of the mean extraction distance, the model was considerably improved ($R^2$-adj = 26.0%), whereas further additions of variables resulted in rather modest improvements. Twelve out of 15 variables entered in the stepwise regression significantly contributed, but did not increase the level of explained variance to more than 34% (Appendix 4). The only variables that did not contribute were 6 and 9, and the interaction between 31 and 32. It is notable that the load capacity was entered as the very last variable in the stepwise regression.

The analyses indicate that productivity decreased with higher mean extraction distance, difficult terrain conditions, number of assortments at landing, expected daylight limitations, on forest land owned by non-industrial private forest (NIPF) owners and in lodgepole pine thinnings.

Further, productivity in thinnings was positively influenced by load capacity, the total volume harvested, harvested volume per hectare, mean stem size, and use of adjustable load space. Similarly as for final fellings, forwarders with a high load capacity had generally higher productivity at all extraction distances (Figure 4), and the effect varied depending on the extraction distance (Table 6). Compared to final felling, the differences due to load capacity were rather small (Figure 4).

### ***Conversion from productive to scheduled time***

In planning situations, it is generally important to estimate the productivity per hour that the machines are planned to work ($m^3$/SMh), while the productivity excluding delays ($m^3$/PMh) may be of less interest. The delay times recorded in the data (Table 4) provide indications of the lowest possible decrease in productivity following transformation from $m^3$/PMh to $m^3$/SMh. For instance, harvesters with 30 $m^3$/PMh productivity in final felling will have, on average, a productivity of less than 23.5 $m^3$/SMh (30 × 0.783). Since some delay time might not have correctly accounted for in the reporting (delay time when machines' systems are deactivated might not have been correctly entered manually), the combination of reported productivity per PMh and data in Table 4 provides the upper limits of the productivity per SMh.

## **Discussion**

### ***Comparison with previous harvester models***

In this study, productivity models were constructed based on the largest dataset used to date.

The harvester productivity levels (model type *i*) were consistent with recent Nordic findings (Nurminen et al. 2006; Brunberg 2007), but considerably higher than levels observed in earlier studies, indicating that productivity has increased over time, probably mainly due to technological improvements that have made the machines used faster and more reliable (Nordfjell et al. 2010). It is possible that differences in definitions of time concepts, cf. for instance Björheden (1991) and IUFRO (1995), may account for some of the improvement in productivity over time. Productivity in final felling is

Table 6. Forwarder productivity models ($N$ = 12,552 and 4907 for forwarder productivity in final felling and thinning, respectively).

| Operation | Model category | Variable | Parameter estimate | SE | $p$-value | $R^2$-adj (%) | RMSE |
|---|---|---|---|---|---|---|---|
| Final felling | *i* | Full model | – | – | <0.001 | 35.2 | 0.30 |
| | | Intercept | 0.327 | 0.103 | 0.001 | | |
| | | (Ln(MFD))$^2$ | −0.073 | 0.002 | <0.001 | | |
| | | Ln(Mean stem size) | 0.188 | 0.006 | <0.001 | | |
| | | Ln(MFD × Load capacity) | 0.636 | 0.018 | <0.001 | | |
| | *ii* | Full model | – | – | <0.001 | 35.6 | 0.30 |
| | | Intercept | 0.462 | 0.104 | <0.001 | | |
| | | (Ln(MFD))$^2$ | −0.070 | 0.002 | <0.001 | | |
| | | Ln(Mean stem size) | 0.186 | 0.006 | <0.001 | | |
| | | Ln(MFD × Load capacity) | 0.607 | 0.018 | <0.001 | | |
| | | Adjustable load space | 0.045 | 0.005 | <0.001 | | |
| | *iii* | Full model | – | – | <0.001 | 43.4 | 0.28 |
| | | Intercept | 0.641 | 0.098 | <0.001 | | |
| | | (Ln(MFD))$^2$ | −0.056 | 0.002 | <0.001 | | |
| | | Ln(Mean stem size) | 0.176 | 0.005 | <0.001 | | |
| | | Ln(MFD × Load capacity) | 0.435 | 0.017 | <0.001 | | |
| | | Adjustable load space | 0.044 | 0.005 | <0.001 | | |
| | | Ln(Total harvested volume) | 0.058 | 0.002 | <0.001 | | |
| | | Ln(Harvested volume per ha) | 0.094 | 0.004 | <0.001 | | |
| | | Ln(Terrain roughness × Slope) | −0.074 | 0.004 | <0.001 | | |
| | *iv* | Full model | – | – | <0.001 | 43.9 | 0.28 |
| | | Intercept | 0.650 | 0.097 | <0.001 | | |
| | | (Ln(MFD))$^2$ | −0.057 | 0.002 | <0.001 | | |
| | | Ln(Mean stem size) | 0.178 | 0.005 | <0.001 | | |
| | | Ln(MFD × Load capacity) | 0.448 | 0.017 | <0.001 | | |
| | | Adjustable load space | 0.042 | 0.005 | <0.001 | | |
| | | Ln(Total harvested volume) | 0.060 | 0.002 | <0.001 | | |
| | | Ln(Harvested volume per ha) | 0.113 | 0.005 | <0.001 | | |
| | | Ln(Terrain roughness × Slope) | −0.072 | 0.004 | <0.001 | | |
| | | Ln(Assortments at landing) | −0.121 | 0.011 | <0.001 | | |
| Thinning | *i* | Full model | – | – | <0.001 | 26.4 | 0.28 |
| | | Intercept | 2.798 | 0.179 | <0.001 | | |
| | | (Ln(MFD))$^2$ | −0.029 | 0.003 | <0.001 | | |
| | | Ln(Mean stem size) | 0.296 | 0.010 | <0.001 | | |
| | | Ln(MFD × Load capacity) | 0.166 | 0.032 | <0.001 | | |
| | *ii* | Full model | – | – | <0.001 | 29.4 | 0.27 |
| | | Intercept | 2.318 | 0.181 | <0.001 | | |
| | | (Ln(MFD))$^2$ | −0.028 | 0.003 | <0.001 | | |
| | | Ln(Mean stem size) | 0.259 | 0.011 | <0.001 | | |
| | | Ln(MFD × Load capacity) | 0.149 | 0.031 | <0.001 | | |
| | | Ln(Total harvested volume) | 0.046 | 0.004 | <0.001 | | |
| | | Ln(Harvested volume per ha) | 0.074 | 0.011 | <0.001 | | |
| | | Ln(Terrain roughness × Slope) | −0.050 | 0.007 | <0.001 | | |
| | *iii* | Full model | – | – | <0.001 | 33.4 | 0.27 |
| | | Intercept | 2.366 | 0.176 | <0.001 | | |
| | | (Ln(MFD))$^2$ | −0.024 | 0.003 | <0.001 | | |
| | | Ln(Mean stem size) | 0.244 | 0.011 | <0.001 | | |
| | | Ln(MFD × Load capacity) | 0.098 | 0.031 | 0.001 | | |
| | | Ln(Total harvested volume) | 0.152 | 0.007 | <0.001 | | |
| | | Ln(Harvested volume per ha) | 0.067 | 0.011 | <0.001 | | |
| | | Ln(Terrain roughness × Slope) | −0.050 | 0.007 | <0.001 | | |
| | | Ln(Assortments at landing) | −0.111 | 0.006 | <0.001 | | |

Note: models are for Ln(y), where $y$ = productivity in $m^3$/PMh. The coefficient (intercept) is not corrected for logarithmic bias, and should thus be increased by $RMSE^2/2$ when estimating y (see section 3.3).

now (remarkably) approximately double the level recorded ca. 20 years ago by Kuitto et al. (1994) (Figure 2). In fact, the thinning models presented here and the one published by Nurminen et al. (2006) tally with the 25-year-old model for final felling described by Brunberg (1995), giving more than double the levels reported by Heinimann (2001) for harvesters operating in both thinning and final fellings (<12 $m^3/PMh_{15}$ in stands with a mean stem size of <0.6 $m^3$). Compared to recent thinning studies, the current models resulted in considerably higher productivity, probably due to the somewhat unconventional thinning methods employed by SCA (thinning with intermediate harvester passages) and the focus of previous studies on small harvesters (Sirén & Aaltio 2003) or only first thinning (Purfürst 2009).

Although not easily comparable due to differences in resolution and variables used, the productivity levels found in final felling seem to be considerably higher than of those recently reported for Russia (Gerasimov et al. 2012) as well as by a spruce harvesting model for Italy (Spinelli et al. 2010). However, the levels given by the Italian model for poplar stands (Spinelli et al. 2010) seems to agree with current models, which in turn are considerably lower than the levels modelled for Monterey pine (*Pinus radiata*) harvests in Australia (Strandgard et al. 2013), where the mean tree sizes (>2$m^3$) were greater than those for the current study.

### *Comparison with previous forwarder models*

Forwarding work is intrinsically dependent on more interacting variables than harvesting work. Thus, the level of variance explained by the forwarding model was comparably low. This is most likely due to rather high uncertainties in the mainly manually assessed and reported related variables, which might explain why the automatically measured and reported mean stem size was (surprisingly) found to be the most strongly influential variable for forwarder productivity in thinning (Appendix 4). The higher accuracy of mean stem size measurements might have made it more valuable for predictions than other more directly related variables. The extraction distances, for instance, were not based on measurements of actually driven distances, but on simple assessments prior to the harvesting work. These assessments are normally used in the planning and follow-up of the work, due to their simplicity, but have been found to be highly inaccurate (Femling 2010, Tiger 2012) in specific stands. Thus, it is not surprising that extraction distance was surpassed in this specific dataset by other, more correctly recorded variables, despite the well-known strong relationship between extraction distance and productivity.

It is not easy to compare the productivity models presented here with previously published models, partly because of the larger number of variables involved in the models presented here, and partly because few previous studies have addressed forwarder productivity. At a transport distance of 100 m, the productivity in final felling was ca. 24 $m^3$/PMh for a forwarder with a load volume capacity of 14 $m^3$, which is less than the ca. 27 $m^3$/PMh reported by Nurminen et al. (2006) and the ca. 26 $m^3/PMh_{15}$ reported by Brunberg (2004) for equally large load volumes and distances. However, at 500 m with a load volume of 14 $m^3$, the productivity reported here of ca 18 $m^3$/PMh tallies with both the 19 $m^3$/PMh reported by Nurminen et al. (2006) and the 17 $m^3/PMh_{15}$ reported by Brunberg (2004). Thus, our models seem to indicate that forwarder productivity was fairly similar in the studied operations and the cited findings. Further noteworthy aspects are that we found that the difference in productivity between load capacities decreased slightly with extraction distance, in both final felling and thinning (Figure 3). A rather stable relationship between load capacities is consistent with the findings of Kuitto et al. (1994), whereas Nurminen et al. (2006) found indications that the differences increase with distance. The latter is consistent with theoretical expectations, since the longer the distance the more advantageous it should be to take larger loads each time. However, in our empirical data, the opposite, somewhat counterintuitive, observation was made, probably due to the inaccuracies in the estimations of extraction distances, as discussed above.

### *Strengths and weaknesses*

This study faced a rather unusual challenge when modelling forest machine productivity – a dataset being so large that most of the many possible predictive variables significantly contributed to the models. Compared to having too little data to find significant effects of possibly influential variables, having superfluous data is naturally a more desirable situation. It, nevertheless, creates new demands on the modelling process. Here, we used both a knowledge-based and an automated modelling approach to explore the data and to sieve out the most influential variables. However, a word of caution regarding automated methods is in order: they do not take into account knowledge that human model builders may have about the data and the conditions the models are built for. With that in mind, an automated process might be a helpful tool when building models using large datasets. Further, a limitation of the approach to use large automatically collected datasets for production modelling is the low level of knowledge and control of each studied operation due to the lack of on-site observations. For this study, this has presented some difficulties in the separation of erroneous records in the data from unusual but correct observations, which can be seen in Table 1 where many of the reported min–max ranges correspond to the outlier criteria used to generate the datasets. Consequently, it is advisable for anyone interested in applying the reported models to use the reported percentiles (10th and 90th) rather than the min–max ranges when assessing if the conditions that the models were developed in are similar to the conditions where the models are supposed to be applied.

The significant effects of a multitude of factors on productivity in this study is not surprising, since productivity is previously known to be influenced by, for instance, tree characteristics (Visser & Spinelli 2012), work methods (Manner et al. 2013) and operator skills (Purfürst & Erler 2011). However, this emphasizes the need to have well-adapted and updated models to provide accurate predictions of the forest operations. Automated data-gathering might improve the potential to generate such models, but also introduces some limitations. As mentioned in the Introduction, a general limitation of large-scale data-gathering is that quantity is achieved at the expense of quality and control. The development and implementation of systems for standardizing and controlling data-gathering will probably improve data quality, but at additional cost; and it will probably not remove all errors. Moreover, standards alone do not result in standardized data. For instance, Purfürst (2009) found that methods used to implement the StanForD standard for data recording (Anon 2010) differ between harvester manufacturers and substantial efforts were required to pool data recorded by the different systems prior to analyses. Such variation did not cause any problems in the analyses presented here, since SCA constructed their follow-up system and software independently, long before the StanForD standard was developed. However, as can be seen in Table 1 and in Figure 1, the gathered data included a considerable proportion of values that were either manually assessed or measured and later manually entered into the system by a large number of people. Inevitably, such manual transcription is accompanied by some data entry errors, just as the automatic recording of data is accompanied by some recording errors (arising from adjustments and calibration anomalies) as well as data transfer errors. However, since the data gathered in many cases were used to calculate payments for the contractors, there were substantial incentives to control and correct the data for both the contractors and forest company. Nevertheless, the data relating to between 11% and 16% of the stands clearly included gaps or erroneous data (Table 3). Thus, there is an equally clear need for either data selection (outlier reduction) and/or methods that have minimal sensitivity to erroneous data.

During the analysis, there was a general need to transform data to natural logarithms to fulfil regression prerequisites, and thus to correct for logarithmic bias when retransforming. This is quite common practice, but had some unwanted effects on the models since logarithmic transformation forces the models through the origin of the graph. This is naturally unfortunate for forwarding models, since their productivity intrinsically ought to increase with decreasing extraction distance and not exhibit such behaviour shown in Figure 3, where models turn towards the origin for extraction distances less than 50–100 metres. Thus, the models are unreliable at such short distances. However, this should be of minor concern in practical applications since such short distances are rare. In fact, only ca. 1% of the volume (3% of the stands) included in this study had an extraction distance of less than 100 metres and only 0.06 % of the volume (0.22% of the stands) had a distance of less than 50 metres. For the harvesting models, a similar issue arises since these models include the squared natural log of the mean stem size (in order to achieve normality of the error distribution), a variable that introduces a bias to the predictions for mean stem sizes above 1 $m^3$. However, only 0.13% of the volume (0.24% of the stands) in the final felling dataset had a mean stem size above 1 $m^3$, which should make this a minor concern for applications of the models to similar conditions as the study was carried out in.

Several of the variables used in this study can hardly be considered as good models of the underlying factors, but rather as indications on areas of interest for developing further improved productivity models. Such areas include machine configuration (indicated by significance of variables adjustable loading space, harvester size, harvester head size, accumulating harvester head, maximum cutting diameter, and harvester head weight), type of operation (indicated by significance of variables seed tree harvest, logging residue recovery adaption, abnormal operation, and lodgepole pine), stand complexity (indicated by significance of total harvested volume, and sites owned by non-industrial private forest owners), and environmental factors (indicated by significance of snow obstruction, and daylight limitation).

In our study, we focussed on the mean productivity per stand (as did, for instance, Heinimann 2001 and Purfürst & Lindroos 2011). However, in traditional time studies and also in many recent studies that used automatically collected data (e.g. Strandgard et al. 2013; Gerasimov et al. 2013), the traditional focus is on time consumption per tree with models of productivity measuring $m^3$ per time unit derived from tree-level data. Both options have their advantages and disadvantages, depending on purpose and usage, and the space available here does not allow for further elaboration. However, the development of automated data-gathering will most likely increase the modelling at stand level, since it facilitates previously difficult data-gathering.

### *Conclusions and practical applications*

This study contributes updated productivity models based on the largest sample of harvester and forwarder work in CTL final felling and thinning considered to date. The observed models conform reasonably well to recent productivity models, and indicate that the productivity of harvesters has increased quite rapidly over recent decades.

The study also shows that forest companies are currently able to gather large amounts of follow-up data during routine operations. Thus, by collecting data from their own operations, companies could create their own predictive productivity models and continuously update them to accommodate, for instance, the company-specific conditions relating to, for instance, technical advances, changes in operator skills etc. This will most likely improve the accuracy of their operational planning and costing procedures, as well as the control of work performed.

Ideally, the data gathered should be error-free, but, in reality, datasets are seldom (if ever) completely correct, and it is often difficult to distinguish between errors and unusual, but valid, observations. Hence, removing errors requires a careful balance between rigidity and representability, to ensure that just the right amount of information is retained.

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## Appendix 1: Harvester final fellings

| Number in Table 1 | Variable name | Parameter | Step in the bidirectional stepwise regression analysis 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Constant | | 3.609 | 3.138 | 3.174 | 3.341 | 3.154 | 3.172 | 3.231 | 3.328 | 3.307 | 2.602 | 2.525 | 2.5 |
| 1 | $(\mathrm{Ln(Mean\ stem\ size)})^2$ | Coefficient | −0.2027 | −0.1935 | −0.1947 | −0.097 | −0.0718 | −0.0716 | −0.08 | −0.0748 | −0.0744 | −0.0766 | −0.0751 | −0.0746 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 3 | Ln(Total harvested volume) | Coefficient | | 0.0677 | 0.0743 | 0.0815 | 0.0719 | 0.0744 | 0.068 | 0.0588 | 0.0593 | 0.0569 | 0.0578 | 0.0597 |
| | | *p*-value | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 4, 5 | Ln(Terrain roughness × Slope) | Coefficient | | | −0.0774 | −0.0769 | −0.0811 | −0.0779 | −0.0846 | −0.0827 | −0.0789 | −0.081 | −0.079 | −0.0801 |
| | | *p*-value | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 1 | Ln(Mean stem size) | Coefficient | | | | 0.307 | 0.381 | 0.377 | 0.355 | 0.362 | 0.366 | 0.348 | 0.345 | 0.347 |
| | | *p*-value | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 2 | Ln(Harvested volume per hectare) | Coefficient | | | | | 0.0611 | 0.0569 | 0.0593 | 0.055 | 0.0562 | 0.0515 | 0.059 | 0.0615 |
| | | *p*-value | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 16 | Ln(Difficult trees) | Coefficient | | | | | | −0.0382 | −0.0418 | −0.0407 | −0.0418 | −0.0395 | −0.0349 | −0.0346 |
| | | *p*-value | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 7 | Non-industrial private land | Coefficient | | | | | | | −0.0629 | −0.0763 | −0.0775 | −0.0783 | −0.0857 | −0.0849 |
| | | *p*-value | | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 12 | Abnormal operation | Coefficient | | | | | | | | −0.1001 | −0.1011 | −0.1006 | −0.101 | −0.1022 |
| | | *p*-value | | | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 30 | Accumulating harvester head | Coefficient | | | | | | | | | 0.0685 | 0.0768 | 0.077 | 0.0766 |
| | | *p*-value | | | | | | | | | <0.001 | <0.001 | <0.001 | <0.001 |
| 28 | Ln(Harvester head weight) | Coefficient | | | | | | | | | | 0.104 | 0.111 | 0.112 |
| | | *p*-value | | | | | | | | | | <0.001 | <0.001 | <0.001 |
| 15 | Ln(Undergrowth) | Coefficient | | | | | | | | | | | −0.00671 | −0.00635 |
| | | *p*-value | | | | | | | | | | | <0.001 | <0.001 |
| 10 | Logging residue recovery adaptation | Coefficient | | | | | | | | | | | | −0.0404 |
| | | *p*-value | | | | | | | | | | | | <0.001 |
| 17 | S machine size × Ln(Mean stem size) | Coefficient | | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | | |
| 11 | Seed tree recovery | Coefficient | | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | | |
| 25 | L harvester head ×Ln(Mean stem size) | Coefficient | | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | | |
| 6 | Ln(Bucked assortments) | Coefficient | | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | | |
| 22 | XXXL machine size × Ln(Mean stem size) | Coefficient | | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | | |
| 19 | L machine size × Ln(Mean stem size) | Coefficient | | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | | |
| 23 | S harvester head × Ln(Mean stem size) | Coefficient | | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | | |
| 29 | Ln(Cutting diameter) | Coefficient | | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | | |
| 27 | XXL harvester head × Ln(Mean stem size) | Coefficient | | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | | |
| 21 | XXL machine size × Ln(Mean stem size) | Coefficient | | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | | |
| 9 | Expected snow limitation | Coefficient | | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | | |
| 8 | Expected daylight limitation | Coefficient | | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | | |
| | Statistical metrics for each stepwise regression: | S | 0.287 | 0.276 | 0.272 | 0.27 | 0.267 | 0.266 | 0.264 | 0.262 | 0.261 | 0.26 | 0.259 | 0.259 |
| | | R-Square | 55.15 | 58.68 | 59.72 | 60.41 | 61.11 | 61.66 | 62.15 | 62.65 | 63.08 | 63.27 | 63.43 | 63.51 |
| | | R-Square (adj) | 55.14 | 58.68 | 59.71 | 60.4 | 61.09 | 61.64 | 62.13 | 62.63 | 63.06 | 63.24 | 63.39 | 63.47 |

*(continued)*

Appendix 1: *(Continued)*.

| Number in Table 1 | Variable name | Parameter | Step in the bidirectional stepwise regression analysis 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Constant | | 2.554 | 2.462 | 2.422 | 2.46 | 2.64 | 2.683 | 2.567 | 2.383 | 1.883 | 1.981 | 1.985 | 1.98 |
| 1 | (Ln(Mean stem size))$^2$ | Coefficient | −0.0738 | −0.0784 | −0.0791 | −0.08 | −0.0786 | −0.0771 | −0.0787 | −0.0791 | −0.0834 | −0.0824 | −0.0821 | −0.0821 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 3 | Ln(Total harvested volume) | Coefficient | 0.0596 | 0.0607 | 0.0606 | 0.061 | 0.0614 | 0.0615 | 0.0615 | 0.0612 | 0.0608 | 0.061 | 0.0608 | 0.0607 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 4, 5 | Ln(Terrain roughness × Slope) | Coefficient | −0.0804 | −0.0809 | −0.0807 | −0.0809 | −0.0804 | −0.0807 | −0.0809 | −0.0809 | −0.0803 | −0.0806 | −0.0805 | −0.0806 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 1 | Ln(Mean stem size) | Coefficient | 0.35 | 0.327 | 0.33 | 0.327 | 0.334 | 0.337 | 0.333 | 0.334 | 0.315 | 0.32 | 0.321 | 0.321 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 2 | Ln(Harvested volume per hectare) | Coefficient | 0.0619 | 0.0738 | 0.0743 | 0.0751 | 0.074 | 0.0746 | 0.0738 | 0.0737 | 0.0739 | 0.0734 | 0.074 | 0.074 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 16 | Ln(Difficult trees) | Coefficient | −0.0351 | −0.0345 | −0.0343 | −0.0338 | −0.0332 | −0.0334 | −0.033 | −0.0325 | −0.0326 | −0.0324 | −0.0322 | −0.0322 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 7 | Non-industrial private land | Coefficient | −0.0847 | −0.0829 | −0.0824 | −0.081 | −0.0807 | −0.0811 | −0.0813 | −0.0817 | −0.0817 | −0.0824 | −0.0807 | −0.0791 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 12 | Abnormal operation | Coefficient | −0.1014 | −0.0925 | −0.0919 | −0.0913 | −0.0921 | −0.0917 | −0.093 | −0.0923 | −0.0915 | −0.092 | −0.0924 | −0.0924 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 30 | Accumulating harvester head | Coefficient | 0.0749 | 0.0747 | 0.0701 | 0.0693 | 0.0698 | 0.0772 | 0.0774 | 0.0766 | 0.0777 | 0.0803 | 0.0799 | 0.0796 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 28 | Ln(Harvester head weight) | Coefficient | 0.105 | 0.104 | 0.11 | 0.111 | 0.086 | 0.08 | 0.096 | 0.05 | 0.06 | 0.042 | 0.042 | 0.043 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 15 | Ln(Undergrowth) | Coefficient | −0.00626 | −0.00626 | −0.00616 | −0.00564 | −0.00549 | −0.00556 | −0.00548 | −0.00546 | −0.00552 | −0.00566 | −0.00561 | −0.00553 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 10 | Logging residue recovery adaptation | Coefficient | −0.0403 | −0.0413 | −0.0411 | −0.0398 | −0.0393 | −0.0394 | −0.0393 | −0.0401 | −0.0401 | −0.0404 | −0.0404 | −0.0411 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 17 | S machine size × Ln(Mean stem size) | Coefficient | 0.071 | 0.071 | 0.066 | 0.069 | 0.072 | 0.074 | 0.091 | 0.091 | 0.09 | 0.09 | 0.09 | 0.091 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 11 | Seed tree recovery | Coefficient | | 0.057 | 0.057 | 0.056 | 0.054 | 0.054 | 0.054 | 0.053 | 0.055 | 0.054 | 0.055 | 0.054 |
| | | *p*-value | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 25 | L harvester head ×Ln(Mean stem size) | Coefficient | | | −0.012 | −0.0123 | −0.0134 | −0.0139 | −0.0158 | −0.0199 | −0.0188 | −0.0207 | −0.0207 | −0.0207 |
| | | *p*-value | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 6 | Ln(Bucked assortments) | Coefficient | | | | −0.046 | −0.048 | −0.049 | −0.046 | −0.045 | −0.044 | −0.048 | −0.048 | −0.048 |
| | | *p*-value | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 22 | XXXL machine size × Ln(Mean stem size) | Coefficient | | | | | −0.025 | −0.0258 | −0.0234 | −0.0294 | −0.0367 | −0.0469 | −0.0468 | −0.0468 |
| | | *p*-value | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 19 | L machine size × Ln(Mean stem size) | Coefficient | | | | | | 0.0153 | 0.016 | 0.0164 | 0.0181 | 0.0184 | 0.0184 | 0.0186 |
| | | *p*-value | | | | | | 0.002 | 0.001 | 0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 23 | S harvester head × Ln(Mean stem size) | Coefficient | | | | | | | −0.0251 | −0.0362 | −0.0492 | −0.0491 | −0.049 | −0.0486 |
| | | *p*-value | | | | | | | 0.003 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 29 | Ln(Cutting diameter) | Coefficient | | | | | | | | 0.12 | 0.222 | 0.231 | 0.229 | 0.229 |
| | | *p*-value | | | | | | | | 0.007 | <0.001 | <0.001 | <0.001 | <0.001 |
| 27 | XXL harvester head × Ln(Mean stem size) | Coefficient | | | | | | | | | 0.0218 | 0.025 | 0.0248 | 0.0249 |
| | | *p*-value | | | | | | | | | 0.001 | <0.001 | <0.001 | <0.001 |
| 21 | XXL machine size × Ln(Mean stem size) | Coefficient | | | | | | | | | | −0.0165 | −0.0166 | −0.0168 |
| | | *p*-value | | | | | | | | | | 0.002 | 0.002 | 0.002 |
| 9 | Expected snow limitation | Coefficient | | | | | | | | | | | −0.0117 | −0.0202 |
| | | *p*-value | | | | | | | | | | | 0.025 | <0.001 |
| 8 | Expected daylight limitation | Coefficient | | | | | | | | | | | | 0.019 |
| | | *p*-value | | | | | | | | | | | | 0.001 |
| | Statistical metrics for each stepwise regression: | S | 0.259 | 0.259 | 0.259 | 0.259 | 0.258 | 0.258 | 0.258 | 0.258 | 0.258 | 0.258 | 0.258 | 0.258 |
| | | R-Square | 63.56 | 63.6 | 63.64 | 63.68 | 63.72 | 63.75 | 63.77 | 63.8 | 63.83 | 63.86 | 63.87 | 63.91 |
| | | R-Square (adj) | 63.52 | 63.56 | 63.6 | 63.63 | 63.67 | 63.7 | 63.72 | 63.74 | 63.77 | 63.79 | 63.81 | 63.84 |

## Appendix 2: Harvester thinnings

| Number in Table 1 | Variable name | Parameter | Step in the bidirectional stepwise regression analysis | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
| | Constant | | 3.235 | 3.247 | 3.038 | 3.003 | 3.016 | 3.000 | 3.053 | 3.076 | 2.775 | 2.753 | 3.046 |
| 1 | (Ln(Mean stem size))$^2$ | Coefficient | −0.1587 | −0.1526 | −0.1515 | −0.148 | −0.1477 | −0.1477 | −0.1478 | −0.147 | −0.1504 | −0.1521 | −0.0873 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 24 | Medium harvester head × Ln(Mean stem size) | Coefficient | | 0.0406 | 0.0414 | 0.0383 | 0.0382 | 0.0374 | 0.0378 | 0.0367 | 0.0364 | 0.0338 | 0.0337 |
| | | *p*-value | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 3 | Ln(Total harvested volume) | Coefficient | | | 0.034 | 0.0408 | 0.0444 | 0.0448 | 0.0404 | 0.0418 | 0.0401 | 0.0404 | 0.042 |
| | | *p*-value | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 16 | Ln(Difficult trees) | Coefficient | | | | −0.0353 | −0.0322 | −0.0327 | −0.0367 | −0.0321 | −0.0317 | −0.0299 | −0.0315 |
| | | *p*-value | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 4, 5 | Ln(Terrain roughness × Slope) | Coefficient | | | | | −0.0417 | −0.0426 | −0.0475 | −0.0442 | −0.0437 | −0.0433 | −0.0427 |
| | | *p*-value | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 30 | Accumulating harvester head | Coefficient | | | | | | 0.0497 | 0.0497 | 0.0496 | 0.0505 | 0.0519 | 0.0511 |
| | | *p*-value | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 7 | Non-industrial private land | Coefficient | | | | | | | −0.0394 | −0.0494 | −0.0531 | −0.0556 | −0.0555 |
| | | *p*-value | | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 15 | Ln(Undergrowth) | Coefficient | | | | | | | | −0.0083 | −0.0095 | −0.0098 | −0.0094 |
| | | *p*-value | | | | | | | | <0.001 | <0.001 | <0.001 | <0.001 |
| 14 | Ln(Stems per hectare) | Coefficient | | | | | | | | | 0.0549 | 0.0581 | 0.0609 |
| | | *p*-value | | | | | | | | | <0.001 | <0.001 | <0.001 |
| 20 | XL machine size × Ln(Mean stem size) | Coefficient | | | | | | | | | | −0.0204 | −0.0203 |
| | | *p*-value | | | | | | | | | | <0.001 | <0.001 |
| 1 | Ln(Mean stem size) | Coefficient | | | | | | | | | | | 0.294 |
| | | *p*-value | | | | | | | | | | | <0.001 |
| 6 | Ln(Bucked assortments) | Coefficient | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | |
| 13 | Lodgepole pine | Coefficient | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | |
| 26 | XL harvester head × Ln(Mean stem size) | Coefficient | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | |
| 17 | S machine size × Ln(Mean stem size) | Coefficient | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | |
| 22 | XXXL machine size × Ln(Mean stem size) | Coefficient | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | |
| 9 | Expected snow limitation | Coefficient | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | |
| 21 | XXL machine size × Ln(Mean stem size) | Coefficient | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | |
| 2 | Ln(Harvested volume per hectare) | Coefficient | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | |
| 8 | Expected daylight limitation | Coefficient | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | |
| 29 | Ln(Cutting diameter) | Coefficient | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | |
| 28 | Ln(Harvester head weight) | Coefficient | | | | | | | | | | | |
| | | *p*-value | | | | | | | | | | | |
| | Statistical metrics for each stepwise regrssion: | S | 0.253 | 0.248 | 0.246 | 0.244 | 0.243 | 0.242 | 0.241 | 0.24 | 0.239 | 0.239 | 0.238 |
| | | R-Square | 57.52 | 59.05 | 59.84 | 60.61 | 60.94 | 61.27 | 61.49 | 61.79 | 62.06 | 62.26 | 62.45 |
| | | R-Square (adj) | 57.51 | 59.03 | 59.82 | 60.58 | 60.9 | 61.22 | 61.43 | 61.73 | 61.99 | 62.18 | 62.36 |

(*continued*)

Appendix 2: *(Continued)*.

| Number in Table 1 | Variable name | Parameter | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Step in the bidirectional stepwise regression analysis | | | | | | | | | | |
| | Constant | | 3.093 | 3.098 | 3.093 | 3.099 | 3.078 | 3.065 | 3.054 | 2.992 | 2.987 | 2.731 | 3.09 |
| 1 | (Ln(Mean stem size))$^2$ | Coefficient | −0.089 | −0.083 | −0.082 | −0.083 | −0.087 | −0.088 | −0.091 | −0.09 | −0.089 | −0.09 | −0.088 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 24 | Medium harvester head × Ln(Mean stem size) | Coefficient | 0.0329 | 0.0328 | 0.0341 | 0.0356 | 0.0352 | 0.0353 | 0.035 | 0.0352 | 0.0352 | 0.0362 | 0.0486 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 3 | Ln(Total harvested volume) | Coefficient | 0.0412 | 0.043 | 0.0426 | 0.0423 | 0.0427 | 0.0426 | 0.0424 | 0.0424 | 0.0424 | 0.0424 | 0.0422 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 16 | Ln(Difficult trees) | Coefficient | −0.0344 | −0.0278 | −0.0271 | −0.0277 | −0.0276 | −0.0273 | −0.0272 | −0.027 | −0.0271 | −0.0275 | −0.0266 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 4, 5 | Ln(Terrain roughness × Slope) | Coefficient | −0.0436 | −0.0434 | −0.0434 | −0.0442 | −0.0445 | −0.0443 | −0.0446 | −0.045 | −0.045 | −0.0442 | −0.0437 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 30 | Accumulating harvester head | Coefficient | 0.0512 | 0.0524 | 0.0513 | 0.0486 | 0.0492 | 0.0479 | 0.0488 | 0.0496 | 0.05 | 0.0497 | 0.0482 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 7 | Non-industrial private land | Coefficient | −0.0498 | −0.0544 | −0.0541 | −0.0535 | −0.0537 | −0.0477 | −0.0483 | −0.049 | −0.0477 | −0.0472 | −0.0471 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 15 | Ln(Undergrowth) | Coefficient | −0.0092 | −0.0094 | −0.0093 | −0.0092 | −0.0092 | −0.0088 | −0.0089 | −0.0094 | −0.0094 | −0.0092 | −0.0092 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 14 | Ln(Stems per hectare) | Coefficient | 0.0623 | 0.0653 | 0.0682 | 0.0666 | 0.0662 | 0.0679 | 0.0673 | 0.054 | 0.054 | 0.054 | 0.054 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 20 | XL machine size × Ln(Mean stem size) | Coefficient | −0.0218 | −0.0226 | −0.0254 | −0.024 | −0.0244 | −0.0245 | −0.0252 | −0.0255 | −0.0254 | −0.0241 | −0.0242 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 1 | Ln(Mean stem size) | Coefficient | 0.292 | 0.311 | 0.316 | 0.309 | 0.292 | 0.286 | 0.272 | 0.264 | 0.266 | 0.262 | 0.267 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 6 | Ln(Bucked assortments) | Coefficient | −0.043 | −0.06 | −0.061 | −0.061 | −0.062 | −0.061 | −0.062 | −0.063 | −0.063 | −0.061 | −0.058 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 13 | Lodgepole pine | Coefficient | | −0.056 | −0.057 | −0.057 | −0.057 | −0.058 | −0.058 | −0.055 | −0.056 | −0.054 | −0.054 |
| | | *p*-value | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 26 | XL harvester head × Ln(Mean stem size) | Coefficient | | | 0.042 | 0.042 | 0.042 | 0.042 | 0.046 | 0.046 | 0.046 | 0.048 | 0.042 |
| | | *p*-value | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 17 | S machine size × Ln(Mean stem size) | Coefficient | | | | 0.037 | 0.036 | 0.036 | 0.036 | 0.036 | 0.036 | 0.031 | 0.035 |
| | | *p*-value | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | 0.004 | <0.001 |
| 22 | XXXL machine size × Ln(Mean stem size) | Coefficient | | | | | −0.154 | −0.151 | −0.153 | −0.148 | −0.147 | −0.14 | −0.166 |
| | | *p*-value | | | | | <0.001 | 0.001 | <0.001 | 0.001 | 0.001 | 0.001 | <0.001 |
| 9 | Expected snow limitation | Coefficient | | | | | | −0.0273 | −0.0269 | −0.0272 | −0.0344 | −0.0342 | −0.0346 |
| | | *p*-value | | | | | | 0.001 | 0.001 | 0.001 | <0.001 | <0.001 | <0.001 |
| 21 | XXL machine size × Ln(Mean stem size) | Coefficient | | | | | | | −0.086 | −0.082 | −0.082 | −0.077 | −0.084 |
| | | *p*-value | | | | | | | 0.004 | 0.006 | 0.006 | 0.011 | 0.006 |
| 2 | Ln(Harvested volume per hectare) | Coefficient | | | | | | | | 0.031 | 0.032 | 0.033 | 0.033 |
| | | *p*-value | | | | | | | | 0.011 | 0.009 | 0.008 | 0.007 |
| 8 | Expected daylight limitation | Coefficient | | | | | | | | | 0.0156 | 0.0156 | 0.0152 |
| | | *p*-value | | | | | | | | | 0.067 | 0.068 | 0.074 |
| 29 | Ln(Cutting diameter) | Coefficient | | | | | | | | | | 0.061 | 0.277 |
| | | *p*-value | | | | | | | | | | 0.137 | 0.002 |
| 28 | Ln(Harvester head weight) | Coefficient | | | | | | | | | | | −0.182 |
| | | *p*-value | | | | | | | | | | | 0.005 |
| | Statistical metrics for each stepwise regrssion: | S | 0.238 | 0.237 | 0.237 | 0.237 | 0.236 | 0.236 | 0.236 | 0.236 | 0.236 | 0.236 | 0.236 |
| | | R-Square | 62.56 | 62.69 | 62.8 | 62.9 | 63 | 63.09 | 63.15 | 63.2 | 63.22 | 63.24 | 63.3 |
| | | R-Square (adj) | 62.47 | 62.59 | 62.7 | 62.79 | 62.88 | 62.96 | 63.01 | 63.05 | 63.07 | 63.08 | 63.13 |

## Appendix 3: Forwarder final fellings

| Number in Table 1 | Variable name | Parameter | Step in the bidirectional stepwise regression analysis 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | | | | | | | | | | | | | | | | | |
| | Constant | | 3.6591 | −1.0318 | 0.3266 | 0.6632 | 0.557 | 0.51 | 0.5268 | 0.6498 | 0.6062 | 0.996 | 1.0077 | 1.0388 | 0.9878 | 0.9867 | 0.995 |
| 31 | $(\text{Ln(Mean extraction distance)})^2$ | Coefficient | −0.01906 | −0.09171 | −0.07297 | −0.06241 | −0.05855 | −0.05825 | −0.0592 | −0.0567 | −0.0572 | −0.0432 | −0.043 | −0.0429 | −0.0428 | −0.0429 | -0.0429 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 31, 34 | Ln(Mean extraction distance × Load capacity) | Coefficient | | 0.835 | 0.636 | 0.499 | 0.457 | 0.465 | 0.476 | 0.448 | 0.452 | 0.29 | 0.29 | 0.29 | 0.288 | 0.289 | 0.288 |
| | | *p*-value | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 1 | Ln(Mean stem size) | Coefficient | | | 0.1877 | 0.1795 | 0.1734 | 0.1778 | 0.18 | 0.1784 | 0.1785 | 0.1766 | 0.1777 | 0.1757 | 0.1687 | 0.1681 | 0.1687 |
| | | *p*-value | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 3 | Ln(Total harvested volume) | Coefficient | | | | 0.0705 | 0.0548 | 0.0591 | 0.0613 | 0.0605 | 0.0623 | 0.0637 | 0.0615 | 0.0582 | 0.0592 | 0.0592 | 0.0594 |
| | | *p*-value | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 2 | Ln(Harvested volume per hectare) | Coefficient | | | | | 0.0857 | 0.0914 | 0.111 | 0.1127 | 0.1144 | 0.1128 | 0.1142 | 0.1127 | 0.1214 | 0.1216 | 0.1213 |
| | | *p*-value | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 4, 5 | Ln(Terrain roughness × Slope) | Coefficient | | | | | | −0.0779 | −0.075 | −0.0717 | −0.073 | −0.0721 | −0.0747 | −0.0746 | −0.0747 | −0.0747 | -0.0745 |
| | | *p*-value | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 36 | Ln(Assortments at landing) | Coefficient | | | | | | | −0.125 | −0.121 | −0.114 | −0.116 | −0.114 | −0.111 | −0.112 | −0.112 | -0.112 |
| | | *p*-value | | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 35 | Adjustable loading space | Coefficient | | | | | | | | 0.0419 | 0.0417 | 0.0406 | 0.0412 | 0.0408 | 0.0409 | 0.041 | 0.0412 |
| | | *p*-value | | | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 10 | Logging residue recovery adaptation | Coefficient | | | | | | | | | −0.0394 | −0.0388 | −0.0384 | −0.0395 | −0.0401 | −0.0397 | -0.0394 |
| | | *p*-value | | | | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 34 | Ln(Load capacity) | Coefficient | | | | | | | | | | 0.187 | 0.188 | 0.185 | 0.187 | 0.185 | 0.184 |
| | | *p*-value | | | | | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 7 | Non-industrial private land | Coefficient | | | | | | | | | | | −0.0195 | −0.0242 | −0.0228 | −0.0231 | -0.0249 |
| | | *p*-value | | | | | | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 12 | Abnormal operation | Coefficient | | | | | | | | | | | | −0.0332 | −0.0278 | −0.0279 | -0.0273 |
| | | *p*-value | | | | | | | | | | | | <0.001 | 0.001 | 0.001 | 0.001 |
| 11 | Seed tree recovery | Coefficient | | | | | | | | | | | | | 0.041 | 0.042 | 0.041 |
| | | *p*-value | | | | | | | | | | | | | 0.01 | 0.008 | 0.009 |
| 8 | Expected daylight limitation | Coefficient | | | | | | | | | | | | | | −0.0115 | -0.0176 |
| | | *p*-value | | | | | | | | | | | | | | 0.035 | 0.004 |
| 9 | Expected snow limitation | Coefficient | | | | | | | | | | | | | | | 0.0145 |
| | | *p*-value | | | | | | | | | | | | | | | 0.022 |
| | Statistical metrics for each stepwise regression: | S | 0.339 | 0.311 | 0.299 | 0.288 | 0.283 | 0.28 | 0.279 | 0.278 | 0.278 | 0.277 | 0.277 | 0.277 | 0.277 | 0.277 | 0.277 |
| | | R-Square | 16.65 | 29.81 | 35.24 | 39.95 | 41.68 | 43.07 | 43.66 | 43.95 | 44.06 | 44.12 | 44.18 | 44.26 | 44.29 | 44.31 | 44.33 |
| | | R-Square (adj) | 16.64 | 29.79 | 35.22 | 39.93 | 41.66 | 43.04 | 43.62 | 43.92 | 44.02 | 44.08 | 44.13 | 44.2 | 44.23 | 44.24 | 44.26 |

## Appendix 4: Forwarder thinnings

| Number in table 1 | Variable name | Parameter | Step in the bidirectional stepwise regression analysis 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Constant | | 3.26 | 3.715 | 3.484 | 3.209 | 3.206 | 2.89 | 2.916 | 1.977 | 1.976 | 1.949 | 1.94 | 1.813 |
| 1 | Ln(Mean stem size) | Coefficient | 0.3225 | 0.3076 | 0.3034 | 0.2818 | 0.2787 | 0.2498 | 0.25 | 0.251 | 0.251 | 0.244 | 0.245 | 0.243 |
| | | *p*-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 31 | (Ln(Mean extraction distance))$^2$ | Coefficient | | −0.01418 | −0.0153 | −0.01567 | −0.01518 | −0.01518 | −0.01481 | −0.04311 | −0.04312 | −0.04362 | −0.04366 | −0.04358 |
| | | *p*-value | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 3 | Ln(Total harvested volume) | Coefficient | | | 0.0436 | 0.1526 | 0.157 | 0.1536 | 0.1463 | 0.1444 | 0.1448 | 0.1457 | 0.1449 | 0.1439 |
| | | *p*-value | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 36 | Ln(Assortments at landing) | Coefficient | | | | −0.1151 | −0.1151 | −0.1134 | −0.112 | −0.1131 | −0.1135 | −0.113 | −0.1122 | −0.111 |
| | | *p*-value | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 4, 5 | Ln(Terrain roughness × Slope) | Coefficient | | | | | −0.051 | −0.0497 | −0.0563 | −0.0589 | −0.0588 | −0.0579 | −0.0568 | −0.0566 |
| | | *p*-value | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 2 | Ln(Harvested volume per hectare) | Coefficient | | | | | | 0.069 | 0.076 | 0.078 | 0.079 | 0.078 | 0.079 | 0.078 |
| | | *p*-value | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 7 | Non-industrial private land | Coefficient | | | | | | | −0.04 | −0.0403 | −0.0402 | −0.0447 | −0.0453 | −0.0446 |
| | | *p*-value | | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 31 | Ln(Mean extraction distance) | Coefficient | | | | | | | | 0.33 | 0.331 | 0.336 | 0.337 | 0.335 |
| | | *p*-value | | | | | | | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| 8 | Expected daylight limitation | Coefficient | | | | | | | | | −0.0296 | −0.0297 | −0.0297 | −0.0303 |
| | | *p*-value | | | | | | | | | <0.001 | <0.001 | <0.001 | <0.001 |
| 13 | Lodgepole pine | Coefficient | | | | | | | | | | −0.027 | −0.025 | −0.02 |
| | | *p*-value | | | | | | | | | | 0.038 | 0.052 | 0.134 |
| 35 | Adjustable loading space | Coefficient | | | | | | | | | | | 0.0134 | 0.0135 |
| | | *p*-value | | | | | | | | | | | 0.101 | 0.1 |
| 34 | Ln(Load capacity) | Coefficient | | | | | | | | | | | | 0.053 |
| | | *p*-value | | | | | | | | | | | | 0.122 |
| | Statistical metrics for each stepwise regression: | S | 0.3 | 0.281 | 0.278 | 0.269 | 0.268 | 0.267 | 0.266 | 0.266 | 0.266 | 0.265 | 0.265 | 0.265 |
| | | R-Square | 15.48 | 26.02 | 27.76 | 32.11 | 32.8 | 33.38 | 33.69 | 33.91 | 34.08 | 34.14 | 34.17 | 34.2 |
| | | R-Square (adj) | 15.46 | 25.99 | 27.72 | 32.05 | 32.73 | 33.29 | 33.6 | 33.8 | 33.96 | 34 | 34.02 | 34.04 |