**Digital Transformation in Timber Harvesting:**
**An Automated Framework for Productivity**
**and Performance Monitoring in Whole-Tree Harvesting**

by

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# Abstract

The increasing complexity of modern forest operations demands advanced methodologies for productivity assessment. While onboard computers (OBC) and sensor technologies are well-integrated into cut-to-length (CTL) harvesting systems, their adaption in whole-tree (WT) harvesting is limited. The lack of standardized automated data collection in WT operations makes productivity analysis more resource-intensive and reliant on manual data gathering. This research seeks to bridge this gap by leveraging long-term large-scale production data recorded by FPDat II OBC to develop productivity models for felling machines in WT harvesting.

A multi-stage methodology was employed, beginning with a systematic synthesis of key productivity-influencing factors in feller buncher and feller director operations. Subsequently, a validation study assessed the accuracy of FPDat II OBCs in estimating machine time metrics. Building on these findings, a novel approach integrating OBC-generated GNSS data with high-resolution LiDAR-based forest inventory data was developed to automate production analysis. The final phase involved long-term productivity modeling using a heteroscedastic mixed-effects framework to identify the influence of the variables stem size, stems per hectare, volume per hectare and ground slope on productivity.

Results indicate that OBC data loggers provide reliable machine time estimates, with errors in productive time remaining below 1% when appropriate preprocessing thresholds are applied. Integrating GNSS-derived machine tracks with forest inventory data enabled accurate estimations of harvested volume at a machine-level resolution, reducing dependency on manual field measurements. The developed productivity models offer actionable insights on WT felling at the machine- and cutblock-level.

This research contributes to the advancement of digital forest machine connectivity by providing a scalable framework for automated productivity monitoring in WT harvesting. The findings support industry stakeholders in optimizing machine deployment, improving operational planning, and enhancing supply chain efficiency. Future research should explore AI-driven predictive modeling and real-time machine connectivity to further refine productivity assessment methodologies in industrial forestry.

# Lay Summary

The integration of advanced technology in forest operations has enhanced data collection and productivity analysis, especially in mechanized harvesting. Cut-to-length (CTL) systems use onboard computers (OBC) and sensors for real-time tracking, but whole-tree (WT) harvesting has not fully adopted similar automated systems, limiting the ability to gather consistent and reliable data.

In WT harvesting, there is no standard way to collect production data automatically across different machines, making it difficult to analyze and model productivity effectively. While aftermarket data loggers show potential for tracking machine performance, they are not yet widely implemented in WT systems.

This research aims to bridge these gaps by improving data collection, accuracy, and analysis in WT harvesting while leveraging technologies like OBCs and geographic data. The study seeks to develop reliable methods to measure machine productivity and identify performance factors. These advancements will enhance decision-making in sustainable forest management and operational efficiency.

# Preface

The objectives and research questions outlined in this dissertation were formulated in collaboration with the author's supervisory committee and the author. The research chapters included in this work have either been published, or are ready for submission to peer-reviewed journals and conferences, as detailed below.

**Chapter 3 -** Lahrsen, S., Mologni, O., Magalhães, J., Grigolato, S., Röser, D. (2022). Key factors influencing productivity of whole-tree ground-based felling equipment commonly used in the Pacific Northwest. *Canadian Journal of Forest Research, 52*(4), 450–462. https://doi.org/10.1139/cjfr-2021-0266

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The author of this dissertation undertook the primary research for Chapters 3, 5, and 6, including conceptualization, methodology, validation, formal analysis, investigation, data curation, writing the original draft, and visualization. Co-authors contributed to conceptualization, methodology, validation, data curation, and provided feedback on the drafts. For Chapter 4, the author of this dissertation partook in writing the original draft, validation, investigation, formal analysis, data curation, and in reviewing and editing the final draft.

Throughout the writing process, generative AI tools, specifically OpenAI's ChatGPT, were used to support grammar correction and language refinement. All content, interpretations, and conclusions presented in this thesis are solely the result of the author's work.

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## List of Abbreviations

AB – Alberta

AGRIS – Agricultural Science and Technology Information

AIC – Akaike Information Criterion

amsl – Above mean sea level

ANCOVA – Analysis of covariance

ANOVA – Analysis of variance

BC – British Columbia

BEC – Biogeoclimatic Ecosystem Classification

BFGS – Broyden-Fletcher-Goldfarb-Shanno

BIC – Bayesian Information Criterion

CAB – CAB Abstracts, Forest Science Database CABI

CAN – Controller Area Network

CI – Confidence interval

cm – Centimeter

CTL – Cut-to-length

CV – Coefficient of variation

DBH – Diameter at breast height

FB – Feller buncher

FD – Feller director

FERIC – Forest Engineering Research Institute of Canada

FGR – Forest Growers Research

FMC – Forest Machine Connectivity

FPI – FPInnovations

fps – Frames per second

GALILEO – European Satellite Navigation System

GFIS – Global Forest Information Service

GIS – Geographic Information System

GLONASS – Globalnaya Navigatsionnaya Sputnikovaya Sistema

GNSS – Global Navigation Satellite System

GOS – Google Scholar

GPS – Global Positioning System

h – Hour

ha – Hectare

Hz – Hertz

ID – Identification

IUFRO – International Union of Forest Research Organizations

m – Meter

$m^3$ – Cubic meter

MAE – Mean absolute error

mAh – Milliampere-hour

min – Minute

NSR – Nordic Forest Research Council

OBC – On-board computer

OTD – Off-To-Delay

PMH – Productive machine hour

pp – Percentage points

ppm – Pixels per meter

PUB – PubAg, USDA

RMSE – Root mean square error

s – Second

SCP – Scopus

SD – Standard deviation

SE – Standard error

SMH – Scheduled machine hour

t – Metric tonne

TRS – Treesearch, USDA, U.S. Forest Service

UBC – University of British Columbia

USDA – United States Department of Agriculture

WAAS – Wide Area Augmentation System

WCPS – World Confederation of Productivity Science

WOS – Web of Science core collection

WT – Whole-tree

WTD – Work-To-Delay

## Glossary

**Cable yarder** – a machine designed to provide the power needed to extract trees or tree parts using a cable system, typically involving a tower that may be either integrated into the machine or set up as a separate structure

**Cable yarding** – the process of transporting trees or parts of trees using a cable system, partially or fully suspended above the forest floor

**Cable-based harvesting** – harvesting operations in which the primary transportation of trees or logs is performed by machines that use cable systems

**Complete tree harvesting** – also referred to as *total tree harvesting*, a harvesting method that involves harvesting the entire tree, including stump and coarse roots

**Cut-to-length harvesting** – a harvesting method in which the trees are felled, processed, and sometimes sorted at the stump. The resulting short-wood products are subsequently hauled to the roadside, where they are piled separately for secondary transportation (Löffler, 1991)

**Delimbing** – the process removing branches from trees or parts of trees

**Feller buncher** – a machine designed to fell standing trees and arrange them in bunches for easier extraction

**Feller director** – a machine designed to fell standing trees in a controlled and preferred direction

**Forwarder** – a machine designed to move trees or parts of trees by carrying them off the ground on a bunk, typically from the felling site to a roadside landing

**Full-tree harvesting** – used as a synonym for whole-tree harvesting, this method involves felling trees and transporting them to the roadside with branches and tops intact (COST, 2013)

**Green tonne** – one tonne of a biomass product with an unspecified moisture content

**Ground-based harvesting** – Harvesting operations in which the primary transportation is carried out by machines that travel on the ground

**Harvesting method** – distinguishes the form in which the harvested timber is hauled to the landing or roadside

**Harvesting system** – a combination of equipment used to carry out the first two phases (felling and primary transportation) in harvesting operations

**Landing** – a cleared area where harvested products are collected during extraction in preparation for transport to a sort yard, wood product mill or other final destination

**Loader-forwarder** – a machine designated to pick up and move trees or parts of trees in primary transportation

**Mechanized felling** – the process of felling trees using machines, such as harvesters or feller bunchers

**Motion study –** the systematic and critical analysis of working motions with the purpose of describing the motions, eliminating useless motions, and arranging the remaining motions in the best sequence for performing the operations (Bjoerheden, 1995)

**Motor-manual felling** – the process of felling trees using a chainsaw

**Observational study** – a systematic observations of known associations between system inputs and outputs that cannot be actively controlled by the observer, as is possible in experiments. These observations allow for the inference of reasons behind changes in output responses (Heinimann, 2021)

**Observational unit** – an entity for which data are collected and compiled into a single record. A study includes *n* data records, each treated as one observation in the statistical analysis (Heinimann, 2021)

**Operations** – a sequence of processes or functions carried out within production systems to create and deliver a company's products and services (Heinimann, 2021)

**Operations management** – the design, operation, and continuous improvement of systems used to create and deliver a company's products and services (Jacobs and Chase, 2011)

**Oven-dry tonne** – one metric tonne of an absolute dry biomass product (moisture content = 0%)

**Primary transportation -** transportation of logs from the felling site to a landing or roadside

**Processing –** the mechanised topping, delimbing and bucking of stems

**Processor** – a machine that does not fell trees but carries out two or more sequential operations, such as delimbing, bucking, to modify the harvested material's form into products

**Production system** – a unit that can consist of machines, tools, humans, storage buffers, system inputs, and outputs which are interconnected through a defined flow of materials and information, following a specific process scheme or plan (Chryssolouris, 2006)

**Productive machine time** – the portion of the scheduled machine time (work time) that is spent contributing directly to the completion of a specific work task, typically occurring on a cyclic basis. Often expressed in delay-free productive machine hour ($PMH_0$) or productive machine hour, including delays shorter than 15 min ($PMH_{15}$)

**Productivity** – the rate of product output per unit of (typically) time for a production system. A productivity ratio can also be calculated for resources other than time (COST 2013)

**Productivity study** – a study aiming at establishing the rate of productivity within the specified production system (Bjoerheden, 1995)

**Scheduled machine time** – also referred to as *workplace time*, the total time a machine is scheduled to work

**Secondary transportation** – the transportation of logs from the landing or roadside to a wood product mill or other final destination

**Set-up time** – the portion of the change-over time used to prepare the production system for operation at a new site, such as stationing and stabilizing portable equipment, setting up rigging for cable systems, etc. (COST, 2013)

**Skidder** – a machine designed to transport trees or parts of trees by trailing or dragging

**Standard time** – the amount of time a qualified worker, using the appropriate processes and tools, takes to complete a specific job, allowing for personal fatigue and unavoidable delays

**Time study** – the measurement, classification, and systematic analysis of time consumption in work, aimed at increasing the efficiency of the study object by eliminating useless time consumption (Bjoerheden, 1995)

**Tree-length harvesting** – a harvesting method in which the trees are delimbed, topped at the stump, and extracted before crosscutting. It is often mistakenly used as a synonym for whole-tree harvesting (COST, 2013)

**Utilization** – the ratio of productive machine time per scheduled time (work time) in percent

**Whole-tree harvesting** – also referred to as *full-tree harvesting* and sometimes *tree-length harvesting*, the trees are cut and extracted in their full length (all biomass above the stump) to the landing or roadside, where they are processed (Spinelli et al., 2002; COST, 2013; Soman et al., 2020)

**Winch-assist harvesting** – harvesting operations with machines assisted by cables powered by a winch

**Work cycle** – a sequence of work elements repeated for each work object or work piece. A work cycle of higher order may consist of a number of work cycles of lower order (Bjoerheden, 1995)

**Work element** - a sub-division of a work task that is defined by limiting break points

**Work science** - the branch of knowledge associated with work and its measurement, including the work itself, man at work, the machines, tools and other equipment employed in work and the organization and methods of work (Bjoerheden, 1995)

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*To my Family die Lahrsen-Bande: Ingi, Maiky, Mama und Papa – Ich habe euch lieb!*

# Chapter 1 - Introduction

Timber harvesting has a long history in Canada and has become one of the most important industry sectors starting with harvesting timber for shipbuilding in the $16^{th}$-century and later the production of timber, lumber, and paper by the beginning of the $19^{th}$-century (Natural Resources Canada, 2014). After initial timber harvesting with little regulations, more and more restrictions and limitation on timber rights were implemented. In the early to mid-$20^{th}$-century the era of conservation began. During the 1930s several provinces carried out forest inventories which revealed that timber resources were greatly depleted under the existing licensing system, threatening the long-term viability of the industry. The need for a licensing system that ensured sustained-yield forestry practices became obvious. In 1949 the Canada Forestry Act was adopted by the federal government to initiate cost-shared forestry programs with the provinces to ensure controlled harvesting on crown land. By the 1960s most provinces had incentive-based tenure systems in place that regulated forest operation by submission and approval of area-based management plans (Ross, 1997). Since then, forest practices have improved in terms of sustainability (Pearse, 1985). However, public criticism towards timber harvesting operations arose. In the $21^{st}$-century, several additional challenges such as beetle infestations and intense forest fires have increased the pressure on forest management (Bourchier et al., 2015).

Out of the 362 million hectares (ha) of forested land in Canada, 54.4 million ha are found in the province of British Columbia (BC). The total standing volume in BC is estimated to be 11 billion cubic meters ($m^3$) (Gilani and Innes, 2020). Timber harvesting in a commercial manner can be traced back to the 1820s in this province. Since then, timber harvesting has always been a substantial part of the province's economy. Today, BC's forest products make 24% (2022) of the province's export (British Columbia Ministry of Forests, 2024a). In 2021, the employment rate in forestry and timber harvesting, support activities for forestry, pulp and paper product manufacturing, and wood product manufacturing in BC was 55,715 people working in over 7000 businesses (Natural Resources Canada, 2024). The profitability of forest operations is an important factor in maintaining an environmentally, socially, and economically sustainable forest sector and advancing overall forest management practices (Marchi et al., 2018). However, fiber procurement is not the only resource for which BC's forests are managed. Healthy and broad biodiversity in the ecosystem forest, watersheds, carbon sequestration, and recreational needs play an essential role in BC's forestry sustainability goals today. A special responsibility lies in the involvement of First Nations Peoples in any decision-making in forestry.

Over the past two decades, the economically and technically feasible availability of timber resources has declined due to various challenges, including limited investment in intensive silviculture for second-growth forest stands. The effects of climate change (e.g., mild winters and hot dry summers) in combination with past forest management discission such as fire suppression contribute to increasing frequencies and severity of insect pests (Sambaraju et al., 2012) and intensify the risk of forest fires (Wotton et al., 2010). These changes are likely to decrease the active period of harvesting operations and transportation. Furthermore, environmental concerns, recreational demands, and government regulations (e.g., caribou and goshawk habitats (Sutherland, 2020), ungulate winter range (Borth, 2022), visual quality objectives (Southam, 2016), etc.) are putting additional demand and pressures on the timber harvesting land base in BC. The result of this shortage is a significant disruption of existing supply chains, forcing the industry to move its operations into previously underutilized and marginalized forest stands.

During these challenging times, one of the considerable gaps is limited information to forest operations sustainability, productivity, and financial feasibility under changing harvesting conditions (Jensen and Lussier, 2021). These complicated circumstances make it difficult to remain competitive in the international market and the need for cost-efficient, highly productive harvesting solutions is more critical than ever (Abbott et al., 2009). One common way to determine whether harvesting solutions are productive have been detailed productivity studies in which time standards and productivity rates are developed. Time standards for producing specific products generally help to calculate costs and profit, determine the number of machines and operators needed and enhance the scheduling of machines and operations (Stephens and Meyer, 2000). These time standards are set by conducting time studies. A key outcome of these studies is productivity defined as the measure of product output per resource input which in forest operations is normally expressed in units or volume produced per time unit. Modern harvester machines in cut-to-length (CTL) harvesting operations are equipped with sensors that continuously collect stem measurement data in an automated manner, which can be used in time studies to determine productivity (Kemmerer and Labelle, 2021). CTL harvesting involves processing trees directly at the stump, where they are delimbed and cut into predefined lengths before being transported, reducing the need for additional processing at roadside or mills. However, this is not yet the case for the machines used in whole-tree (WT) harvesting in Western Canada (Gingras and Charette, 2017). In contrast, WT harvesting involves felling entire trees and transporting them to centralized processing locations, where they are delimbed and cut, often making it more suitable for large-scale operations but with greater logistical complexity.

New technologies for monitoring machine performance and facilitating communication within the WT harvesting supply chain can address key operational challenges in the forest industry by supporting data-driven forestry. Many stakeholders recognize that advances in technology, digitization, and big data analytics are essential for ensuring the sector's economic and environmental sustainability in the short, medium, and long term (Kemmerer and Labelle, 2021). To optimize resource allocation and improve harvesting machine efficiency, the forest industry requires a better understanding of machine productivity under varying conditions. Consequently, existing productivity models must be updated and adapted to incorporate automated data collection technologies, thereby enhancing WT harvesting operations in BC. Further research is needed to develop new productivity models, algorithms, benchmarking tools, and automated data collection solutions (Strange et al., 2021), which is particularly critical given that WT harvesting remains the predominant harvesting method in BC.

## 1.1 Literature Review

Timber harvesting is a complex linkage of several processes. The equipment used in the different stages of this supply chain depends on the forest type, stand and terrain characteristics, desired products, legal and environmental constraints, availability of technical equipment, and costs (Castro et al., 2016). Over the last decades, the utilization of forests for timber production has developed and is undergoing a trend towards higher grades of mechanization in many parts of the world (Spinelli and Magagnotti, 2011; Parajuli et al., 2020). This development has increased productivity, work safety, and accessibility to difficult terrain (Kellogg and Brink, 1992; Axelsson, 1998; Visser et al., 2014; Castro et al., 2016). As the mechanized harvesting process is a multifaceted operation that includes various combinations of expensive forest machines, it is essential to understand the individual performance and the interactions between multiple machines and phases (She et al., 2018).

Mechanised timber harvesting typically involves cutting trees, processing them into logs, transporting the logs from the stump to a landing or roadside (primary transport), and transportation to a wood product mill or other final destination (secondary transport) (MacDonald, 1999). The order of these phases can differ between harvesting systems and methods. The harvesting system is the combination of equipment used to deploy the first two phases. Various harvesting systems have been developed to implement silvicultural treatments and meet long-term objectives in differing conditions. These systems can deploy either manual, motor manual, partially mechanized, or fully mechanized felling and are historically categorized into ground-based, cable-based, and aerial-based systems depending on the form of primary transport of harvested logs (Heinimann, 2004). The configuration of the components in the harvesting systems should be adapted to the harvesting conditions (Längin et al., 2010). Motor-manual felling in combination with cable-based or aerial-based primary transportation is more commonly deployed on challenging terrain that does not facilitate the use of ground-based felling machines for example (Kühmaier and Stampfer, 2010). Conventional ground-based mechanized felling and primary transportation require safe accessibility of machines to the stand and, for this reason, were traditionally limited to gentle terrain (Horodnic, 2015). However, recent interest in making operations on steep ground safer and more cost-efficient led to the development and implementation of winch-assist technologies that enables ground-based forest machines to access very steep terrain (Visser and Stampfer, 2015). Winch-assist harvesting systems have enabled fully mechanized operations on steep slopes and extended mechanized felling in cable-based systems, thereby limiting the use of cable- and aerial-based systems to only the most extreme and inaccessible conditions.

The harvesting method distinguishes the form in which the harvested timber is hauled to the landing or roadside. Depending on the method, the logs are processed to a different extent at the stump (Längin et al., 2010). There is no agreed definition of terminology for these methods. The following will define terminology used for the context of this dissertation. In the WT method, also referred to as full-tree harvesting and sometimes tree-length harvesting, the trees are cut and extracted in their full length (all biomass above the stump) to the landing, where they are processed (Spinelli et al., 2002; COST, 2013; Soman et al., 2020). This method is one of the most widely used around the world (Längin et al., 2010), and since the implementation of mechanized harvesting in western Canada, the WT method has been a common way for harvesting trees. In the CTL method, the trees are felled, processed, and sometimes sorted at the stump. The short-wood products are then hauled to the roadside, where they are piled separately for secondary transportation (Löffler, 1991). This method is dominant in mechanized harvesting in Europe, especially in Scandinavia (Gellerstedt and Dahlin, 1999). The use of CTL harvesting is increasing rapidly in North America. In eastern Canada, this method has become as important as WT timber harvesting (Labelle et al., 2016). In the western Provinces, including BC, the CTL method has not reached the same level of importance that it has in Eastern Canada. The large-scale implementation of a method new to the area, such as CTL, across the industry is a slow process as it requires investment in new equipment, a higher level of operator training, and the availability of mechanics to service the equipment (Gellerstedt and Dahlin, 1999). Especially in BC, the WT method has a long history and has evolved to be the dominant harvesting method (MacDonald, 1999); no subsequent studies have been published that contradict these findings, however, anecdotal evidence support them.

In mechanized harvesting, the methods require a different number of machines to perform the felling, primary transport, and processing phases of the timber harvesting. A fully-mechanised ground-based CTL harvesting operation typically includes only two machines to deliver the product to the roadside, ready for secondary transportation (Längin et al., 2010; Uusitalo, 2010). A single-grip harvester, equipped with a harvesting head, grabs and fells the tree in the desired direction. In a second step, it delimbs the stem and bucks it into sorts. A forwarder performs the extraction of the short log assortments. The WT method, on the other hand, commonly involves a larger number and variety of machines for different purposes, and it is commonly used in both ground-based and cable-based harvesting systems. For ground-based systems, feller bunchers or feller directors are typical felling machines, skidders or a loader-forwarder are used for primary transportation, and processors or stroke delimbers are involved in processing phase (Table 1.1) (MacDonald, 1999; Uusitalo, 2010; Castro et al., 2016).

*Table 1.1 Overview of the most common machines applied in the WT method with ground-based and cable-based primary transportation.*

| Felling | Primary transportation | Processing |
|---|---|---|
| Feller buncher | Ground-based: | Dangle-head processors or feller-processors |
| Feller directors | Grapple skidders | Stroke-delimbers |
| | Clambunk skidders | |
| | Cable skidders | |
| | Loader-forwarders | |
| | Cable-based: | |
| | Swing yarders | |
| | Tower yarders | |

Both the WT and CTL harvesting methods can be fully mechanized in cable-based systems, where cable yarders are used for primary transportation. While CTL harvesting is technically feasible in cable yarding systems, its application remains highly limited. A variety of different cable systems can be used in combination with grapples to yard the felled trees and logs to landing or roadside, either partially or fully suspended. Typical yarding machines are swing yarders (mobile carriers with booms that swing sideways in both directions) and tower yarders (stationary spars during the yarding phase). A detailed description of the machines introduced in Table 1.1 can be found in Appendix A.

### 1.1.1 Work Study and Machine Performance Measurements

Work studies in scientific management aim to improve production processes through standardizing and optimizing tools, machinery, and equipment, while also enhancing the labor process through worker training, reorganizing salaries, and stabilizing employment and production (Nyland, 1996). Applied approaches within this concept such as time studies, piece-rate wage incentives, and labor control, were established in the early 20$^{th}$-century through publications by Taylor and Gilbreth (Heinimann, 2021). The goal was to reward “a fair day’s work” with “a fair day’s pay” by establishing standard times for compensation (Anson, 1953).

The scientific management of work studies, however, was criticized by labor unions and scholars in the field. They argued that it could diminish workers' skills and undermine their bargaining power, while others within the time study community felt that focusing solely on standard procedures was too restrictive (Nyland, 1996; Smith, 1964). As a result, the World Confederation of Productivity Science (WCPS) was formed. Traditional work studies primarily addressed human or man-machine performance, but the creation of WCPS shifted the focus. Recognizing that manufacturing has evolved into a network process involving numerous suppliers to produce a single type of good or service, productivity studies began to emphasize group, organizational, and network levels (Heinimann, 2021).

Forest Work Science in Forest Sciences has been its own field of research for almost one hundred years with the aim to investigate and improve the production and safety in timber harvesting (Harstela, 1993; Magagnotti et al., 2012). First work studies date back to Branniff (1912), who explored the potential application of scientific management based on time studies within the forestry sector. Ashe (1916) conducted a time study of four key forestry processes: felling and bucking, skidding, loading and hauling, and sawmilling. This study introduced the "piece-volume principle," highlighting that production costs per unit volume increase as the average volume per piece decreases, representing a significant quantitative documentation of this principle for the first time. By 1922, studies comparing tractor and horse skidding found that tractors outperformed horses for skidding distances over 100 meters and for smaller timber sizes, contributing to the acceptance of mechanized timber harvesting (Girard, 1922). In the late 1920s, time studies began to emerge in Germany, notably with the establishment of the Institute of Forest Work Science in 1927. These early studies were based on descriptive statistics, using basic parameters, such as sample means and sample standard deviations (SD), and simple graphics like bar charts and box plots to illustrate data trends.

Around two and a half decades later operational studies in forestry started using inferential statistics such as analysis of variance (ANOVA), analysis of covariance (ANCOVA), or regression models. The introduction of computer-based analysis in the late 1960s, with programs like SPSS and SAS, and the introduction of personal computers in the 1980s, significantly advanced statistical analysis capabilities. Open-source software such as R further made powerful statistical tools widely accessible (Heinimann, 2021).

Contributions to operational efficiency and productivity studies continued to evolve in the 1980s and 1990s. Häberle's work on time study data gathering and analysis focused on model-based approaches and the selection of critical variables (Häberle, 1990). Olsen and Kellogg (1983) compared various time study techniques, concluding that shift-level summaries and stopwatch studies provided the most accurate data on timber harvesting productivity. Further studies highlighted that detailed time studies offer detailed analysis, while they only represent a limited sample of real-world operations. Shift-level studies, on the other hand, tend to reflect actual conditions more broadly but often fail to account for important variables and factors (Olsen et al., 1998).

Through strong international cooperation, scientific networks such as the NSR (Nordic Forest Research Council) and IUFRO (International Union of Forest Research Organizations) were formed (Sundberg, 1988; Magagnotti et al., 2012), and within the international community of forest engineers, general agreements on the goals and methods of work studies were established (Björheden, 1991). With the effort of international researchers, standards for work studies in the forestry sector such as the IUFRO Forest Work Study Nomenclature (Björheden et al., 1995) were agreed upon, and several best practice guides (Samset, 1990; Bergstrand, 1991; Harstela, 1991; Olsen et al., 1998) were made available. Although an international community of forest engineers exists, the development of research in the forestry work science discipline has adapted to local environments, technology, and industry needs. There still seems to be a lack of application of these international standards.

### 1.1.2 Time Studies

Time studies, developed by Taylor at the end of the 19th-century are a core tool of industrial engineering used to develop time standards. These standards, which are part of broader work standards that include quality and dimensions, are essential when establishing new processes, machines, products, working methods, or adjusting work content. Time standards serve multiple purposes: they assist in budget allocation and control, production planning and inventory control, performance evaluation for productivity, and the assessment of alternative methods of operation (Stephens and Meyers, 2000). Today, a time standard is defined as the time required for a well-trained worker, operating at a normal pace, to complete a specific task under defined conditions, including method, material specifications, and equipment used (Bidanda, 2022).

The concept of time studies can be, simplified, described in four steps:

- The work task to be analysed is divided into several elements
- The time that it takes a well-trained worker to perform these elements is measured over several work task cycles
- The averages for element times and cycle time are determined and multiplied by a rating factor (a subjective rating of the workers performance in percent) to obtain the "normal time"
- Finally, allowances for personal needs, rest and unavoidable delays are applied to the "normal time" to obtain "standard time"

In forest operations, the principles of time study are widely applicable. However, challenges arise due to the lack of standardized inputs and outputs, the absence of protocols for statistical analysis, and the varying conditions under which operations occur. Consequently, applying a time standard to operations with fluctuating conditions is difficult.

To establish a standardized time framework for analyzing production systems in an operational forestry context, the Forest Work Study Nomenclature by Björheden et al. (1995) categorizes time, as illustrated in Figure 1.1.

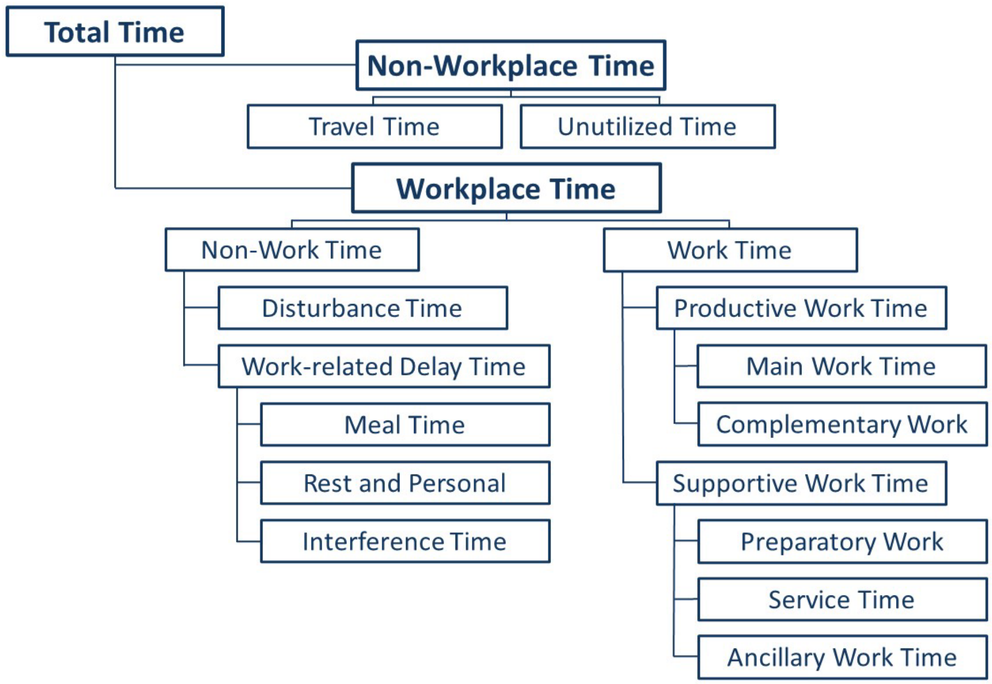


*Figure 1.1 Classification of time in forest operations work studies (adapted from Björheden et al., 1995).*

The total time in this concept is understood as the time of consideration, often calendric time. Non-workplace time refers to the portion of total time spent away from the workplace, including travel time to and from work, as well as unutilized time, such as periods when the worker is off duty. Hence, workplace time is often called scheduled workplace time (Heinimann, 2021). The time that is spent by the observed production system at the work place to directly (productive work time) or indirectly (supportive work time) complete a work task is called work time. Other workplace time in which no work is being completed is referred to as non-work time and can consist of unpredictable work interruptions (disturbance time) and delays such as meal, rest, and personal breaks or interference time in which the production system has to wait for the completion of a different task before work can be continued.

Following this classification of time, two conceptional time units, scheduled machine hours (SMH) and productive machine hours (PMH), have become the most commonly used in forest operations production studies where the observed production system often consists of a single machine and one operator. SMH is used to capture the time in which the machine is scheduled to be productive, while PMH is typically used to describe the efficiency of the machine. The following three time metrics are typically used to describe the efficiency of a production system:

- $PMH_0$ – the delay-free productive machine time that includes only the time that a machine is directly engaged with completing a work task, it is also referred to as work time or raw productive time as $PMH_0$ does not include any work interruptions
- $PMH_{15}$ – the productive machine time that include breaks up to 15 minutes in order to provide a comprehensive and more realistic view of operational efficiency. Short interruptions can be of any nature as long as they do not interfere with the workflow for longer than 15 minutes
- Utilization – is the ratio between productive machine time ($PMH_0$ or $PMH_{15}$ as per definition) and the scheduled machine time

In most time studies, the observed time is classified to identify bottlenecks within the production system or to determine system productivity. This classification contributes to both productivity assessment and the refinement of decision-making processes while also supporting timber harvesting cost analysis. Long-term analyses provide a more accurate reflection of the actual average cost of operations, whereas detailed short-term analyses help identify the influence of process variables on productivity.

### 1.1.3 Productivity Studies

Productivity is commonly defined as the "rate of product output per unit of time for a given production system" (Björheden et al., 1995), making its measurement an indirect process. The input unit time is determined through time studies while the output unit (mass, volume) has to be quantified, usually simultaneously, to calculate the relation between input and output as productivity. In productivity studies, the volume or mass of produced stems, logs or biomass as output units of harvesting operations are typically not measured at the point of harvesting, due to the safety distance that the observant has to keep from the harvesting machines. Depending on the circumstances of the operations and the availability of inventory data, there are different ways to calculate the output using piece counts or length, diameter and weight measurements (Heinimann, 2021), which will be described in more detail in the following section.

The productivity of individual timber harvesting machines or entire systems is generally measured as output ($m^3$ or tonnes)/$PMH_{15}$ (Harstela, 1991). Clear definitions of units are essential for comparison. Stem volume, for instance, can be modeled as a cylinder, a truncated cone, or a parabolic shape. The most commonly used formulas in forestry are the "Smalian," (1-1) "Huber," (1-2) and "Newton" (1-3) formulas:

$$V = A_m \cdot l \tag{1-1}$$

$$V = \frac{A_s + A_l}{2} \cdot l \tag{1-2}$$

$$V = \frac{A_s + 4 \cdot A_m + A_l}{6} \cdot l \tag{1-3}$$

These calculate volume by multiplying the middle cross-sectional area ($A_m$) or the average of the small ($A_s$) and the large end cross section ($A_l$) - with $A_m$ included in the case of "Newton" - with the stem length ($l$). Stem volume can also be specified as volume over bark or under bark, where under bark excludes the bark's volume. Biomass products, such as wood chips or hog fuel, are typically measured in metric tonnes (t), though occasionally in loose $m^3$. Therefore, it is crucial to specify the moisture content of the measured product. Oven-dry tonnes refer to an absolute dry product (moisture content = 0%), whereas the moisture content of green tonnes is undefined and varies depending on species and stage of drying among other factors.

In forestry, productivity studies have traditionally focused on labor or man-machine productivity with a design and improvement focus. However, the primary goal of continuous productivity improvements has diminished, with many studies now describing the productivity state of specific systems within a given context. Due to the complex environment in which most timber harvesting machines work, productivity studies are typically observational studies. Although, many of these studies are systematic observations, statistical analysis of the collected data provides insight on different factors influencing the productivity of timber harvesting such as piece size, ground slope, sylvicultural systems and the operator effect (Björheden, 1991; Ovaskainen et al., 2004; Ovaskainen et al., 2011; Purfürst and Erler, 2011; Magagnotti et al., 2012; She et al., 2018).

### 1.1.4 Production Measurement Technology

The level of granularity and the desired metrics of the productivity and/or time study determines the way in which data is collected. Machine utilization for example is usually derived from shift-level studies (Magagnotti et al., 2012). These studies with lower granularity can be carried out manually through data collection forms filled out by the operators (Spinelli et al., 2012) or automatically through onboard computer (OBC) systems. To acquire accurate utilization information, data must be collected over a period long enough to capture variability on operating conditions. Productivity rates are commonly derived from cycle time, the number of logs felled per cycle, and the average volume per log. (e.g., Alam et al., 2013; Strandgard et al., 2015; Han et al., 2018). Time studies on a cycle or element level analyze the amount of time spent on individual work tasks. These studies require a more detailed observation of the machine operations and the time consumption per cycle or cycle element is typically recorded manually with a standard wristwatch, stopwatch, stopwatch board, or a hand-held computer (Laitila and Väätäinen, 2021). To minimize the risk of errors by researcher during field observations, the operations being studied can also be recorded on video. The recordings can subsequently be analyzed in more suitable environments, such as computer labs (Uusitalo, 2010).

To retrieve a very accurate estimation of machine performance, the volume of each individual tree should be determined prior to the time study. The volume of a standing tree or felled log can be calculated with the common volume formulas, for which trees are measured with calipers or diameter tapes (Magagnotti et al., 2012). The volume of standing trees can also be determined using the diameter at breast height (DBH) and a diameter-height curve, if already developed for the stand (Alam et al., 2013). Each tree should be numbered so that it can be recognized and its volume be attributed to a specific work cycle during the time study. Since conventional methods require extensive planning before conducting a time study and do not fully leverage modern digital technologies, LiDAR scanning, terrestrial photogrammetry, and sensor-based measurement systems are increasingly used to improve data collection efficiency. Another common approach is to estimate average tree volume from inventory data collected through ground-based sampling before harvesting (cruise), ground-based sampling after harvesting (stump-cruise), or aerial data collection methods such as airborne laser scanning or digital photogrammetry (Goodbody et al., 2017). This average volume is then used as a multiplier for the number of stems counted during the study (British Columbia Ministry of Forests, 2021).

Regardless of the level of analysis, a comprehensive work plan should be written prior to the data collection in order to select the study method, study sites, studied machine and work method (Uusitalo, 2010). Further should the productivity study define and describe the input/output measurement units, measurement methods, and measurement models to indirectly calculate parameters of interest for the purpose of replicability (Heinimann, 2021).

As the direct observation and data collection of machines in the field is labour and time intensive and therefore costly, Heinimann (2021) stated the need for automatically recorded work time and productive time of machines in forest operations in order to omit costly fieldwork to collect vast amounts of observations. In response to this long-known lack of digitalization, forestry equipment manufacturers have constantly improved and increased the use of the latest technology on harvesting machines in the form of sensors and OBCs and several research efforts have been made to provide solutions for automated data collection of machine production (Picchio et al., 2019; Venanzi et al., 2023). For instance, modern CTL felling machines are typically equipped with sensor technology that allows them to record the volume of every individual tree felled, saved in a standardized format, updated in 2011 to StanForD2010 and its 4.0 version in 2023 (Skogforsk, 2024). These data are time stamped and can be integrated with Global Navigation Satellite System (GNSS) position data to retrieve individual machine productivity information and volume distribution maps of the area operated in (Lindroos et al., 2015; Hauglin et al., 2017; Noordmeer et al., 2021). Gathered and collected over long-term periods, these data are also commonly used to perform machine productivity modeling and system analysis in different working environments (Palander et al., 2013; Strandgard et al., 2013; Eriksson and Lindroos, 2014; Walsh and Strandgard, 2014; Manner et al., 2016; Olivera et al., 2016; Brewer et al., 2018; Rossit et al., 2019; Liski et al., 2020; Melander et al., 2020; Melander and Risto, 2020; Gonçalves et al., 2021).

Although, felling machines in WT harvesting are equipped with sensor technology and OBCs by manufacturers as well, there is no standard for data collection. Manufacturer specific solutions, however, include John Deere's "Precision Forestry", a combination of TimberManager™ and TimberMatic™ Maps (John Deere, 2023). Tigercat, on the other hand, offers the LogOn™ and RemoteLog™ systems to enable production analytics without reliance on cellular signals, using direct downloading and satellite communication (Tigercat, 2023). Other manufacturers offer comparable solutions.

Researchers tried to find simple GNSS and sensor-based solutions for automated production information that are widely applicable across different machine models and manufacturers.

McDonald and Fulton (2005), for example, installed GNSS units on skidders to determine work cycles based on the GNSS location alone, predicting productive time and distinguishing between different work elements. Using a different preliminary approach of activity recognition, Pan and McDonald (2019) applied machine learning techniques, analysing the diameter of trees cut by feller bunchers, to estimate the harvested volume, basing their calculations on sound recordings. Building on this, Pan et al. (2022) employed a convolutional neural network to analyse the time spent on three different work elements: cutting, piling, and other activities. This preliminary approach to an automated time study, based on audio and visual recordings, however, was not able to account for delays in the calculation of productive machine hours. Complementing these approaches, recent studies have investigated methodologies for activity recognition in forest operations, which in turns allow for the detection of productive time (Keefe et al., 2022). The study by Becker and Keefe (2022) looked at the early stages of developing and validating a smartphone-based system for activity recognition on excavator-based mastication equipment. Other research efforts claimed an investment of resources into machine monitoring solutions that cover a variety of equipment and allow for operational planning in close-to-real-time. These include Silvismart, developed through the Tech4Effect Project (Berg et al., 2019) and Portal, developed by Earth Force (Portal, 2023). However, no literature or practical evidence is yet available about these solutions. While these technological advancements and research efforts mark a substantial progress in digitalizing forest operations, there is no manufacture-agnostic commercial product largely used in the forestry sector to automatically collect production information (Evanson, 2009; Castonguay, 2019).

### 1.1.5 Data Logger OBCs

Since the early 1980s attempts have been made to automatically record and identify time elements of working machines, including delays with data loggers in order to facilitate cost effective data collection on a large scale (Sauder, 1982). Such data loggers are stand-alone OBCs that are capable of recording production information in fully mechanised harvesting independent of the machine make and model. Expending on this technology, Kärhä et al. (2018) used Telmu 100 data loggers to record the productive time of five harwarders, aiming to determine productivity and costs in commercial thinning. Similarly, Harrill et al. (2018) employed Navman GPS navigation devices on winch-assist and steep-slope harvesting machines to measure productive time and utilization, relying solely on ignition status.

FPInnovations (formerly Forest Engineering Research Institute of Canada - FERIC) has led the development of OBCs for remote machine monitoring since the late 1990's, introducing the MicroDAT (Turcotte, 1999) and improving the quality and capabilities of the system through continuous software and hardware updates. This includes the development of MultiDAT Junior and Senior models in the early 2000′s, FPDat in 2011, and FPDat II in 2018 (Brown et al., 2002; Castonguay, 2019). MultiDATs and FPDats, along with additional or integrated components for satellite data transfer (FPCom) and a data management web platform (FPTrak), composed the FPSuite - a comprehensive operational monitoring platform for forest operations (Gingras and Castonguay, 2014). In 2020, Lim Geomatics Inc. acquired the global licensing, operation, and support of FPDat II and FPTrak and since then has been developing a new web platform for data gathering and data processing. MultiDATs and FPDats have been applied in several time studies on different machine types primarily for medium term analysis (typically in the order of a few months) of machine utilization in technical reports (Davis and Kellogg, 2005; Tran, 2008; Evanson, 2009; Nishio, 2010; Strimbu et al., 2013; Strimbu and MacDonald, 2014a; Strimbu and MacDonald, 2014b; Byrne, 2015a; Byrne, 2015b; Rittich, 2015a; Rittich, 2015b; Strimbu, 2015; Rittich, 2016; Dyson, 2017; Plamondon, 2017; Rittich, 2017a; Roy and Rittich, 2017a; Roy and Rittich, 2017b; Strimbu, 2017; Thiel, 2017; Amishev and Dyson, 2018; Belyea et al., 2018; Rittich, 2018; Strimbu and Boswell, 2018), but also in scientific research (Bowker et al., 2010; Laforest and Pulkki, 2011; Strandgard et al., 2011; Laforest and Pulkki, 2014; Botard et al., 2015; Ghaffariyan, 2015; Strandgard and Mitchell, 2015), and graduate studies (Tepylo, 2017). These systems are also extensively and operationally employed in industrial applications, particularly in the Canadian market where by the end of 2023 there were over 1200 active units (Lim Geomatics, personal communication, Jan 5, 2024).

The practicality and wide applicability of FPDat II and its earlier versions led to a broad and common use by various forest companies throughout Canada and the globe. Nevertheless, while the studies of Kellogg et al. (2005), Evanson (2009), Strandgard et al. (2011), and Tepylo (2017) evaluated the usability of the MultiDATs and FPDats, Pellegrini et al. (2013) was the only publication to ever evaluate the accuracy of MultiDAT dataloggers against an in-field time study, monitoring 165 skidder work cycles across three South African cutblocks through direct observations and hand-held computers. No further systematic assessments have been carried out on MultiDATs and/or FPDats data.

OBCs like FPDat II (Figure 1.2) are promising in capturing production metrics such as productive time measured in $PMH_{15}$ through motion sensors and can be installed on forest machines independent of their type, make, and model.


*Figure 1.2 FPDat II On-Board Computer.*

Most data loggers are capable of tracking the machine's movement over time with their integrated GNSS units (Gallo et al., 2021), which provides crucial production information like the area operated in and distance travelled (Botard et al., 2015). Additionally, their ability to transmit data over satellite communication makes OBCs especially useful in remote locations with no cellphone reception. Additionally, several data loggers access the Controller Area Network (CAN) to record internal machine parameters such as actuator movements, hydraulic pressures, flow rates, engine load, and operational states. However, as standalone solutions, these OBCs do not capture volume or number of trees felled. Therefore, OBCs in WT felling often remain confined to time observations, lacking direct volume inputs (Evanson, 2009; Plamondon, 2017), and productivity estimations based on FPDat units are restrained to block-level assessments, using the entire harvested volume and aggregating all machine data. However, leveraging the GNSS position data from OBCs and integrating this information with high-resolution volume distribution maps could create an estimate of the daily production of each machine.

### 1.1.6 Long-Term Productivity Modelling

Due to the longer existence of automated data collection in CTL harvesting, data sets have been compiled by the industry in countries in which CTL is the most common harvesting method (Eriksson and Lindroos, 2014; Rossit et al., 2019; Liski et al., 2020; Gonçalves et al., 2021). Leveraging these large data sets, researchers in northern Sweden developed models to predict harvester and forwarder productivity in CTL operations, including over 700 machines across 20,000 stands. This extensive dataset enabled the creation of robust productivity models, using linear regression based on ordinary least squares (OLS) parameter estimation (Eriksson and Lindroos, 2014). Other big data approaches, including machine learning methods, have also been employed to analyze timber harvesting productivity. The study by Rossit et al. (2019) utilized decision tree techniques to evaluate the effects of DBH, species, shift, and operator on harvester productivity, using 9,941 records from StanForD files. This method allowed for the evaluation of operator performance across different tree sizes, shifts, and species, providing a planning tool for optimal worker allocation (Rossit et al., 2019). The introduced logic was further refined in a subsequent study that tested different decision tree algorithms (Rossit et al., 2024). Liski et al. (2020) compared gradient boosted machine (GBM), support vector machine (SVM), and ordinary least squares (OLS) regression for this purpose predicting the productivity of CTL harvesting operations. Using data from 1,381 observations across 27 operators and 19 harvesters, the study found that mean stem volume was the most significant factor affecting productivity. The best GBM model predicted productivity with $R^2 = 90.2\%$, highlighting the effectiveness of machine learning techniques in productivity modeling (Liski et al., 2020). Machine learning techniques have further been applied to estimate harvesting productivity in Eucalyptus plantations in Southeastern Brazil. By using variables such as average tree volumes, wood volume in the stand, cutting age, spacing, operator experience, and management regime, the study achieved high accuracy in productivity estimates. The approach yielded results with correlation coefficients of 0.98 and 0.97 for training and validation datasets, respectively, demonstrating the efficacy of machine learning in productivity modeling (Gonçalves et al., 2021).

## 1.2 Knowledge Gaps

The commonly used forest machines to carry out WT operations in BC include tracked swing-to-tree feller bunchers (hereafter feller buncher), tracked feller directors (hereafter called feller director), rubber-tired grapple skidder (hereafter called skidder), swing yarders, loader-forwarders, and dangle-head processors (hereafter called processors) (MacDonald, 1999; Plamondon and Brais, 2000). Despite the capability of integrated OBCs to output data, WT harvesting machines still lack manufacturer-agnostic analytical technologies. Moreover, volume information in WT harvesting is not recorded by machine sensors until the wood is processed at the roadside. Given these limitations, there remains a shortage of up-to-date scientific research on WT harvesting productivity in British Columbia, as previous studies are either outdated or do not provide productivity equations.

A general investment to improve this harvesting method by facilitating machine connectivity and data exchange has only been made as part of the Forest Machine Connectivity (FMC) project (Canada's Digital Super Cluster, 2024). In partnership with two major forest products industry companies located in BC and the University of British Columbia (UBC), the Geographic Information System (GIS) software development company, Lim Geomatics, initiated the project to improve productivity monitoring and connectivity across the supply chain, the province, and stakeholders. With its official start in 2020, this recent development highlights the interest and necessity of forestr machine productivity research in BC.

One of the greatest challenges in WT harvesting production assessment is measuring volume and allocating it to individual machines in each harvesting phase. Specifically, it remains difficult to accurately track productivity in the felling and primary transportation phases. To better understand, monitor, and analyse these two phases, reliable methods of volume measurement and allocation are needed.

In addition to volume measurement challenges, ensuring accurate time measurement is critical for productivity analysis; however, the reliability of data loggers remains an open question. Although solutions such as the FPDat technology are widely used, no thorough validation studies have confirmed their accuracy under varied operating conditions over the long term. This knowledge gap in time-measurement accuracy limits the ability to model productivity or reliably compare performance across different machines and sites.

Whereas several studies have investigated factors that influence the productivity of WT harvesting in various international contexts, key factors specific to BC's local conditions need further exploration. A better understanding of individual machine performance is essential for improving the monitoring and optimization of harvesting operations within the timber supply chain. Filling this gap - both in automated production data collection and in robust productivity modeling - will help identify and optimize the key drivers of WT harvesting efficiency in BC.

## 1.3 Research Objectives

As part of the FMC project, this research addresses the complexity of productivity measurement and modeling in WT harvesting - particularly in the felling phase - with the overarching goal of developing a robust, automated solution for measuring and modeling the productivity of WT felling machines in British Columbia. By integrating existing OBC technologies, forest inventory data, and field validation techniques, this work aims to establish a foundation for more accurate and efficient productivity monitoring and analysing in the forest industry.

To achieve this aim, the research is structured around five main objectives:

**first**, to establish a comprehensive knowledge foundation on the key factors influencing productivity and current production measurement methodologies in WT harvesting through a systematic synthesis of existing evidence;

**second**, to develop an innovative protocol to estimate direct work time and productive time, utilizing FPDat II ignition and motion data, and validated its performance;

**third**, to develop integrative logic that combines FPDat II GNSS data with forest inventory data to derive volume metrics critical for productivity calculations;

**fourth**, to validate the fully automated data collection and analysis approach by directly comparing its performance with traditional in-field methods;

**fifth**, to utilize long-term, automatically collected productivity data to build models that investigate the influence of key variables affecting WT harvesting productivity in BC over wide range of harvesting scenarios.

Alongside these modeling efforts, the dissertation provides a step-by-step methodological guide detailing data preparation, outlier handling, and mixed-effects modeling workflows, ensuring replicability and adaptability for large-scale productivity analyses. Additionally, this research lays the foundation for a benchmarking platform developed by FMC partner organizations by establishing the underlying concepts, logic, and algorithms needed to predict and compare machine performance. While local industry collaborators are anticipated to be early adopters, the insights generated will also benefit forest companies worldwide that seek to monitor harvesting machine performance remotely, thereby supporting BC's evolving forest industry and facilitating a transition to advanced, technology-driven practices.

Each research chapter of this research addresses one important step toward the development of a fully automated solution for collecting production information and estimating the productivity of feller bunchers in WT harvesting.

To meet the research objectives, the following four research questions will be answered with dissertation:

1. Which are the key variables influencing the productivity of whole-tree (WT) felling machines? (Objective 1)
2. How can machine production time metrics be accurately derived from data collected with commercially available data loggers? (Objective 2)
3. How effectively and consistently can key production metrics be automatically estimated for WT felling machines using data loggers integrated with forest inventory data? (Objectives 3 and 4)
4. How can productivity models for WT felling machines be developed and improved using long-term production data from data loggers? (Objective 5)

## 1.4 Dissertation Overview

Following the introduction, **Chapter 2** provides a description of the study sites, the observed machines and the key data collection methodologies that were applied in Chapters 4 and 5. **Chapter 3** is the first research chapter, in which a systematic synthesis of current evidence on WT felling machine productivity is conducted to identify the key productivity-influencing factors of feller bunchers and feller directors. In **Chapter 4** the on-board computer (OBC) technology FPDat II is analysed for its precision in measuring time metrics for different machines applied in WT harvesting in BC including feller bunchers. **Chapter 5** then applies the findings of Chapter 4 in a productivity study of feller bunchers based on remotely collected FPDat II data integrated with forest inventory data in three forest operations across BC. The results are compared with conventional productivity studies based on data collected through detailed in-field studies. **Chapter 6** builds on Chapter 5 by leveraging a large dataset of remotely collected production reports for exploratory productivity model building at BC province wide scale. The influence of five key variables - stem size, volume per hectare, stem density, ground slope, and cutblock size - on the productivity of feller bunchers is analysed at daily machine- and cutblock-level. Finally, **Chapter 7** concludes the dissertation by highlighting key findings, innovations, limitations, and suggesting avenues for future research.

# Chapter 2 - Material and Methods

A total number of six extensive observational in-field studies for data collection were carried out. In the following, the study sites, the observed machines, and the data collection methodology are described in detail. Chapters 4 and 5 utilise these collected data to different extends for their analysis section.

## 2.1 Study Sites Description

The data collection took place in 8 different ordinary clear-cutting operations located in BC, Canada, between June 2022 and November 2022. Seven cutblocks were located in Coastal BC on Vancouver Island and one was situated in the central interior portion of the province (Figure 2.1).

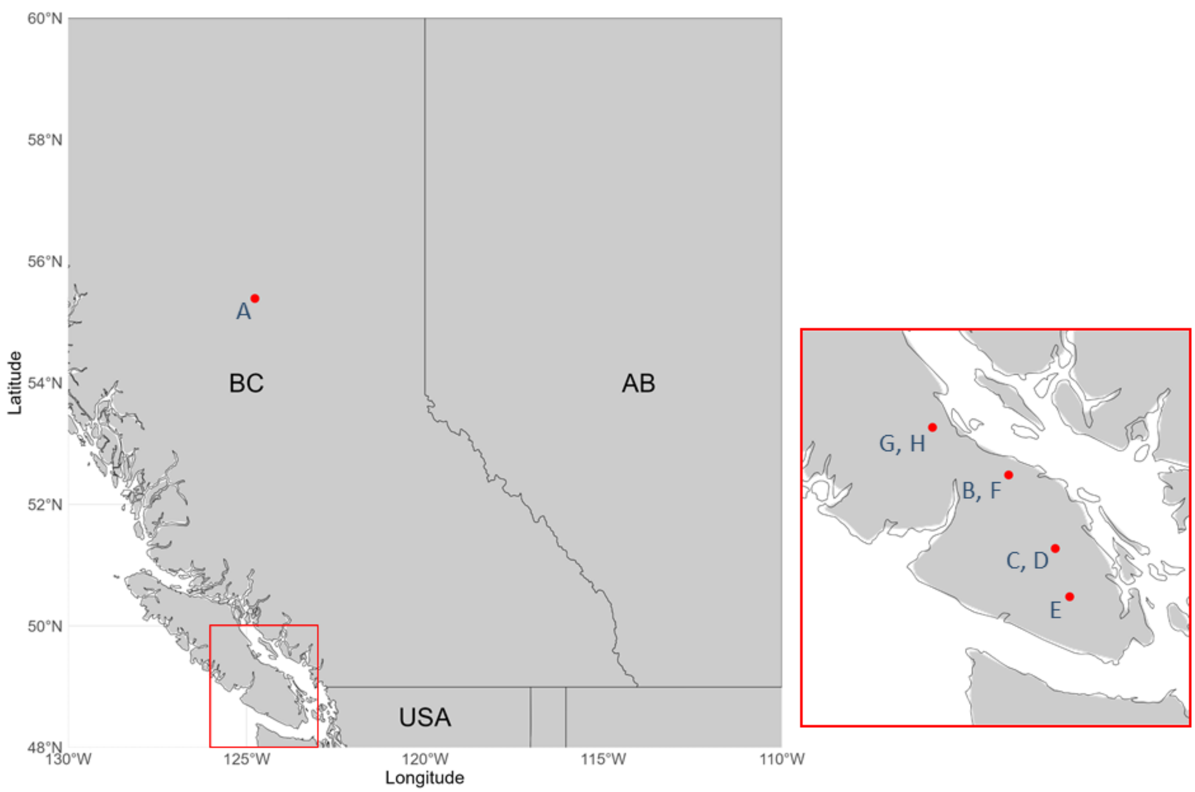


*Figure 2.1 Map visualising the locations of study sites in BC, Canada.*

The cutblocks ranged in size from 18 to 150 ha, with ground slopes averaging between 3.4% and 28.1%. Stand densities varied between 365 and 550 m3/ha (inventory data was only partially available for cut blocks D and E). All cutblocks distributed in BC's coastal forests were located in the Coastal Western Hemlock Biogeoclimatic Ecosystem Classification (BEC) zone in moist to very dry climate and were consisting of common coniferous tree species for this zone: Western Hemlock (*Tsuga heterophylla* (Raf.) Sarg.), Douglas-fir (*Pseudotsuga menziesii* subsp. *menziesii* (Mirb.) Franco), and Western Redcedar (*Thuja plicata* Donn ex D.Don). The cutblock in the central part of the interior of the province was located in the Engelmann Spruce – Subalpine Fir BEC zone in a moist and very cold climate, consisting of zone-typical tree species: Subalpine Fir (*Abies lasiocarpa* (Hook.) Nutt.) and Engelmann Spruce (*Picea engelmannii* Parry ex Engelm.) (Forest Service British Columbia, 2023). Detailed species compositions were not available for the cut blocks E and H.

A summary of site and stand characteristics of the three cutblocks is reported in Table 2.1.

*Table 2.1 Site and stand characteristics of the observed cutblocks A to H.*

| Site and stand characteristics | Cutblock A | Cutblock B | Cutblock C | Cutblock D | Cutblock E | Cutblock F | Cutblock G | Cutblock H |
|---|---|---|---|---|---|---|---|---|
| Geographical area | Interior | Coastal | Coastal | Coastal | Coastal | Coastal | Coastal | Coastal |
| Block size (ha) | 150.1 | 16.9 | 50.8 | 37 | 58.3 | 17.7 | 56.5 | 27.2 |
| Harvested volume ($m^3$) | 53 383 | 7 244 | 26 618 | 19 314 | 25 978 | 8 232 | 27 516 | 12 385 |
| Volume per hectare ($m^3$/ha) | 356 | 469 | 550 | 522 | 465 | 475 | 531 | 485 |
| Avg. stem volume ($m^3$) | 0.55 | 1.17 | 0.68 | - | 0.75 | - | 0.59 | 0.37 |
| Stand density (stems/ha) | 649 | 400 | 812 | - | 620 | - | 907 | 1300 |
| Species composition[a] (%) | Bl 52, Se 48 | Fdc 74, Hw 12, Cw 11, Plc 3 | Fdc 60, Hw 38, Cw 2 | - | Fdc 80, Hw 10, Ba 5, Cw 5 | Fdc 40, Hw 25, Cw 20, Bg 5, Mb 5, Ss 5 | Fdc 80, Hw 15, Cw 5 | - |
| Soil description | dry to wet, sensitive | dry to wet, sensitive | mostly dry | dry to wet, sensitive | dry to wet, sensitive | wet, sensitive | mostly dry | mostly dry |
| BEC zone[b] | ESSFmv3 | CWHxm1 | CWHxm1 | CWHxm1 | CWHmm1 | CWHxm1 | CWHmm2 | CWHmm2 |
| Avg. ground slope (%) | 11.5 | 3.4 | 16.7 | 28.1 | 14.8 | 3.6 | 20 | 22 |
| Elevation (m amsl) | 177 | 474 | 453 | 416 | 586 | 132 | 143 | 771 |
| Monitored phase[c] | F, PT | F | F | L | F | PT | P | PT |
| Monitored machines | FB1, FB4, GS1, GS2, LL3 | FB2 | FB3 | LL4 | FB3 | LL2 | PR1 | LL1 |

[a] Species codes used in BC: Ba – Amabilis fir (*Abies amabilis* Douglas ex J.Forbes); Bg – Grand fir (*Abies grandis* (Douglas ex D.Don) Lindl); Bl – Subalpine fir (*Abies lasiocarpa* (Hook.) Nutt.); Cw – Western Red Cedar (*Thuja plicata* Donn ex D.Don); Fdc – Douglas Fir (*Pseudotsuga menziesii* subsp. *menziesii* (Mirb.) Franco); Hw – Western Hemlock (*Tsuga heterophylla* (Raf.) Sarg.); Mb – Bigleaf maple (*Acer marcophyllum* Pursh); Plc – Lodgepole Pine (*Pinus contorta* subsp. *contorta* Douglas ex Loudon); Se – Engelmann Spruce (*Picea engelmannii* Parry ex Engelm.); Ss – Sitka spruce (*Picea sitchensis* (Bong.) Carrière) (BritishColumbia Ministry of Forests 2024b)

[b] BEC zones: CWHmm2 – Coastal Western Hemlock, Moist Maritime, Montane; CWHxm1 – Coastal Western Hemlock, Very Dry Maritime, Eastern; CWHmm1 – Coastal Western Hemlock, Moist Maritime, Submontane; ESSFmv3 – Engelmann Spruce - Subalpine Fir, Moist Very Cold, Omineca;

[c] Work phases: F = felling; L = loading; P = processing; PT = primary transportation

## 2.2 Machines Description

Although this dissertation focuses mainly on felling machines, the examined machines for the analysis of Chapter 4 also included log loaders, grapple skidders and a processor to increase the number of data observation points. Despite their different roles, the principal for FPDat II recognition of ignition and motion events is the same for all machines.

A total of 11 different machines employed for WT ground-based felling, primary transport, processing, and loading were monitored (Table 2.2), including:

- four tracked swing-to-tree feller bunchers with circular saw felling heads: FB1, FB2, FB3, and FB4
- two four-wheel grapple skidders: GS1 and GS2
- four tracked log loaders, with specific uses as follows: LL1 and LL2 served as loader-forwarders (i.e., hoe-chuckers, one of which in winch-assist operations), LL3 supported skidding operations as a decking machine and LL4 functioned as a truck loader
- one tracked dangle-head processor that cleared landings for a grapple yarder, processed trees, and loaded trucks: PR1

*Table 2.2 Details of the observed pieces of equipment including Machine type, Year of manufacturing (Year), Carrier Make/Model/Trim, Work phase, Cutblock.*

| Machine ID | Machine type | Year | Carrier Make/Model/Trim | Work phase[a] | Cutblock |
|---|---|---|---|---|---|
| FB1 | Feller buncher | 2021 | Tigercat X870D | F | A |
| FB2 | Feller buncher | 2014 | Tigercat L870C | F | B |
| FB3 | Feller buncher | 2022 | John Deere 959M | F | C, G |
| FB4 | Feller buncher | 2022 | Tigercat X870D | F | A |
| GS1 | Grapple skidder | 2021 | Tigercat 632H | PTS | A |
| GS2 | Grapple skidder | 2022 | Tigercat 632H | PTS | A |
| LL1 | Log loader | 2021 | CAT 568 LL | PTLF | H |
| LL2 | Log loader | 2021 | John Deere 3156G | PTLF | H |
| LL3 | Log loader | 2015 | John Deere 3754D | PTLF | D |
| LL4 | Log loader | 2017 | Tigercat 880 | PTD | A |
| LL5 | Log loader | 2005 | Madill 3800C | L | E |
| PR1 | Processor | 2019 | CAT 558 LL | P, L | F |

[a]Work phases: F = felling; L = loading; P = processing; PTD = primary transportation decking; PTLF = primary transport loading-forwarding; PTS = primary transport skidding

## 2.3 Data Collection

The majority of the data collection for this dissertation consisted of in-field direct observations, as well as remote tracking. The field data collection focused on monitoring the timber harvesting operations through direct observations, video recording, GNSS machine tracking, and drone imagery for process tracking. While the remote data collection was enabled through FPDat II data loggers. These methodologies introduced in this section were fully applied in Chapter 5, while Chapter 4 employed only some of these methods for their analysis (Table 2.3). A detailed description can be found in the individual chapters.

*Table 2.3 Application of data collection methods in dissertation chapters.*

| Data collection Method | Chapter 4 | Chapter 5 |
|---|---|---|
| Direct observations | X | X |
| In-field video recordings | X | X |
| GNSS machine tracking | - | X |
| Drone imagery | - | X |
| Remote data collection with FPDat II | X | X |

### 2.3.1 In-Field Data Collection

Videos were captured using GoPro® HERO10 action cameras, mounted on the front windows of the monitored machines' cabins. The cameras recorded at a resolution of 1080 ppm and a rate of 30 fps and were connected to power banks (20000 mAh) to ensure sufficient battery life for a whole day of continuous recording. Direct observations by the authors also facilitated the integration of significant events and delays into the analysis. Considering the Hawthorne effect, which describes how a study participant's behavior may change when they know they are being observed, the authors made efforts to remain out of sight as much as possible (Figure 2.2).

*Figure 2.2 Action camera installed in the cabin of a feller buncher, view from the outside (left) and inside (middle) of the machine. GNSS handheld device in an impact- and weather-resistant box on a machines' roof (right).*

GNSS handheld devices (Garmin® eTrex22x, Garmin® 64) secured in impact- and weather-resistant boxes were placed on the machines' roofs and used to record changes in machine position at a frequency of 1 Hz (Figure 2.2). All equipment installed on the machines was taken off for data transfer after every shift and reinstalled before the next shift.
A consumer-type drone (DJI® Mini2), used to record images at a resolution of 12 megapixels, captured each cutblock at the beginning of the observation on the first day and at the end of every shift. The images were taken along a pre-determined grid programmed with the software Map Pilot Pro (version 5.5.4). An 80% lateral and longitudinal overlap between consecutive images was chosen to allow for high precision orthomosaic photo processing, following an adaption of the approach introduced by Hung et al. (2019).

### 2.3.2 Remote Data Collection

All investigated machines were instrumented with FPDat II data loggers, installed by trained technicians prior to the observation. These data loggers can record ignition status (Recorder: ON/OFF), motion status (Motion: ON/OFF) and position of the machine.

The ignition status changes when the machine is turned on or off. When the ignition (Recorder) is ON, the motion sensor determines whether the machine is actively moving by detecting accelerations over a predefined threshold. If movement exceeds this threshold, the motion status is recorded as 'Motion: ON'; otherwise, it is recorded as 'Motion: OFF'. This allows differentiation between operational movement ('Recorder: ON' and 'Motion: ON') and idling with machine vibrations ('Recorder: ON' and 'Motion: OFF'). To ensure accuracy, machine-specific motion thresholds were calibrated during installation using configuration software. Status changes in ignition and motion are recorded as discrete event logs.

Location data is captured by the data loggers' integrated GNSS functionality. The units support signals from GPS, the Russian Globalnaya Navigatsionnaya Sputnikovaya Sistema (GLONASS), and the European GALILEO system, while also utilizing Wide Area Augmentation Systems (WAAS) for improved accuracy.

The FPDat II data loggers also include three additional channels capable of recording CAN data, including engine parameters such as fuel consumption. A tablet can be connected to the system for operator input and real-time production monitoring, though these additional features were not utilized in this study.

For data transmission, the integrated FPCom system sends recorded data via satellite communication every hour. This is facilitated by the Iridium network, which transmits data packages to a cloud server. While GNSS location is continuously measured, position points are only recorded if the machine exceeds either a 60-minute interval or moves more than 25 meters from the last recorded point by default. This setting was chosen by the collaborating industry partners to minimize data transmission costs.

## 2.4 Data Analysis

The data analysis methods varied across chapters and are therefore not described in detail here but are outlined within the respective chapters. However, all analyses were conducted using the R programming language within the RStudio environment (version 23.06.0). Table 2.4 provides an overview of the R packages utilized, along with their respective references and the chapters in which they were applied.

*Table 2.4 Overview of the R-packages applied in this dissertation, detailing the version, chapters in which they were applied and scientific reference.*

| R-Package | Chapters applied | Reference |
|---|---|---|
| ggplot2 (version 3.4.2) | 3;4;5;6 | Wickham, 2016 |
| dtplyr (version 1.3.1) | 4 | Wickham et al., 2023b |
| dplyr (version 1.1.2) | 4;5;6 | Wickham et al., 2023a |
| tidyR (version 1.3.1) | 5 | Wickham et al., 2024 |
| data.table (version 1.14.8) | 5 | Dowle and Srinivasan, 2023 |
| DHARMa (version 0.4.6) | 5 | Hartig, 2022 |
| nlme (version 3.1.162) | 5;6 | Pinheiro et al., 2023 |
| emmeans (version 1.9.0) | 5;6 | Lenth, 2023 |
| lme4 (version 1.1.35.1) | 5;6 | Bates et al., 2015 |
| purrr (version 1.0.2) | 6 | Wickham and Henry, 2023 |
| sf (version 1.0.16) | 6 | Pebesma and Bivand, 2023 |

# Chapter 3 - Key Factors Influencing Productivity of Whole-Tree Ground-Based Felling Equipment Commonly Used in the Pacific Northwest

## 3.1 Background and Objectives

To understand productivity measurement, common productivity rates and key factors that influence the productivity in WT harvesting an analysis of the existing evidence is crucial. Two main motivations made this chapter an important part of this dissertation. For one, there has been no synthesis done on current knowledge in the productivity of felling machines in WT harvesting that systematically collected and categorized existing research results and created a data base on meta data of productivity influencing factors. And second, building a knowledge base of methodologies used to collect machine productivity forms the foundation for the development of an automatic solution for production data collection.

This chapter aims to identify all the significant factors that influence the productivity of feller bunchers and feller directors. The applied systematic approach highlights the abundance and global distribution of evidence on the performance of these two felling machine types and thereby identifies the most important factors that must be taken into consideration for varying harvesting scenarios. It further enables drawing a conclusion of which factors need to be studied to increase understanding to improve the harvesting productivity prediction in the Pacific Northwest.

## 3.2 Material and Methods

The synthesis of evidence was conducted using a systematic approach to gather existing knowledge in the form of scientific publications and technical reports. The methodology included preparation, search, screening, data extraction, and analysis stages.

### 3.2.1 Search For Evidence

The search for current evidence was carried out on the following bibliographic databases and search engines, with subscriptions of the UBC and the University of Padova.

- Web of Science core collection (WOS)
- CAB Abstracts, Forest Science Database – CABI (CAB)
- Scopus (SCP)
- PubAg, USDA – United States Department of Agriculture (PUB)
- Treesearch, USDA, U.S. Forest Service (TRS)
- Global Forest Information Service (GFIS)
- Agricultural Science and Technology Information (AGRIS)
- IUFRO on-line literature database (IUFRO)

A scoping exercise was conducted on WOS, CAB, and PUB. First, a single keyword search and a result analysis were applied. In the next phase, keywords were combined into search strings which were tested to cover a broad, yet specific scope. After a substantial number of search results was obtained, two refined search strings were used to find evidence on WOS, SCP, CAB, and AGRIS:

*Search string 1*

((Forest*) OR (“Forest Operations”) OR (“Forest Utilization”) OR (“Forest Management”) OR (Silviculture) OR (Logging) OR (Harvesting)) AND ((Machine) OR (Mechanized) OR (Mechanised)) AND ((“Whole tree”) OR (Whole-tree) OR (“Full tree”) OR (Full-tree) OR (“Tree length”) OR (Tree-length)) AND ((Productivity) OR (Efficiency) OR (“Time study”) OR (“Time and motion”) OR (“Work study”) OR (“Work method study”) OR (“Observational study”) OR (“Time and output study”)) NOT ((“Hand falling”) OR (“Hand felling”) OR (“Motor-manual”))

*Search string 2*

((Feller-buncher) OR (Feller buncher) OR (Feller-director) OR (Feller director)) AND ((Productivity) OR (Efficiency) OR ("Time study") OR ("Time and motion study") OR ("Work study") OR ("Work method study") OR ("Observational study") OR ("Time and output study"))

Search string 1 addressed a broad machine-unspecific scope that included productivity studies in WT harvesting operations. The term "tree-length" is included in the string, as it is sometimes used synonymously with WT (e.g., Thompson, 2003; Visser and Stampfer, 2015; Pan and McDonald, 2019). Search string 2 targeted productivity studies in a machine-specific scope. For the remaining databases (PUB, TRS, GFIS, IUFRO), the search strings had to be adjusted for compatibility with the search tools.

The web-based search engine Google Scholar (GOS) has proven to be a good resource for gray literature (Haddaway et al., 2015) and was used to obtain additional results. The output of results from each query is user-dependent and can vary any time a search with identical search strings is conducted. To extract the results aggregated from Google Scholar as citations, the software Publish or Perish©, version 7.27.2949.7581 was used (Harzing, 2007).

Finally, two relevant organizational libraries were included in the search for evidence:

- Forest Growers Research (FGR), New Zealand
- FPInnovations (FPI), Canada

FGR and FPI are research institutions that publish technical reports internally and publicly. Both are relevant sources for grey literature. Since neither of these web-page-implemented search engines accepts Boolean operators such as "OR", "NOT" or "AND", or truncations, the search strings were not used. Instead, two searches were conducted on each of the organizational websites using the search terms "feller buncher" and "feller director."

The reference management software Mendeley© Desktop, version 1.19.8 was used to assemble a library of the search results (Elsevier, 2021). All of the results from the sources mentioned above were combined, and the software-integrated tool "duplicate removal" was applied.

### 3.2.2 Screening

After duplicates were removed, the Mendeley© library was exported, and the web-based systematic review managing software Covidence© was used for the title and abstract screening process (Covidence, 2021). A full-text screening followed. Results that passed the first screening stage were retrieved online, to the extent possible. The screening process was conducted by the author only, which made a consistency check unnecessary.

At all stages of the screening process, the following inclusion/exclusion criteria were applied:

- Eligible harvesting systems: whole-tree
    - Exclude: cut-to-length (unless studied in comparison to WT harvesting)
- Eligible influencing factors: any factor that influences the studied machine productivity
- Eligible silvicultural treatments: clear-cutting, shelterwood-cutting, single-selective-cutting, seed-tree-cutting, patch-cutting, retention-cutting, commercial thinning
    - Exclude: pre-commercial thinning, coppice, short-rotation plantation
- Eligible study approaches: elemental time and motion studies, machine simulator studies, shift-level studies
- Eligible outcomes: volume per time unit, time per cycle, time per volume unit
- Eligible study types: peer-reviewed journal articles, technical reports, doctoral dissertations, working papers, conference proceedings
    - Exclude: review articles
- Eligible languages: English
- Eligible machine types: tracked swing-to-tree machines equipped with a circular saw feller buncher head or feller director head
    - Exclude: rubber tire or drive-to-tree machines and processor heads (unless studied in comparison to tracked feller bunchers or feller directors)

Short-rotation plantation and coppice harvesting studies were excluded since they involve the management of woody biomass on agricultural land, which cannot be compared to traditional forest utilization (Faasch and Patenaude, 2012). Productivity studies on harvesting systems do not always specify the involved machines in their title or abstract. Therefore, results that remained unclear in their content were included in the full-text screening. After the full-text screening, the included results were compiled for data extraction.

### 3.2.3 Data Extraction

Of the included results, the information shown in Table 3.1 was extracted and collected in a Microsoft® Excel spreadsheet, if available.

The meta-data was extracted by only the author to maintain consistency. If needed, reported productivity rates, stem volumes, and DBH were converted from the imperial unit system (i.e., inches, feet, acre) into metric units. Board feet were converted into $m^3$ according to a fixed conversion factor of 0.0023597 (Rowlett, 2018). Productivity rates reported in mass were not converted into volume due to the lack of species and region-specific conversion rates. Whenever a result contained more than one study, each was recorded as an individual entry in the database.

*Table 3.1 Categories of extracted information and referring units.*

| Information | Extracted unit |
|---|---|
| Bibliographic information | source database, title, keywords, abstract, author, journal, year, language, publication type, DOI |
| Country | Country name |
| Location | name of closest town, altitude, latitude/longitude |
| Forest type | monocultural coniferous plantation, monocultural deciduous plantation, mixed-coniferous, mixed-deciduous |
| Stand density | Trees/ha |
| Ground slope | Percent |
| Average tree size, e.g., DBH, volume, etc. (standing trees and/or harvested logs, as reported) | Centimeters (cm), $m^3$ |
| Method of determining tree size | sample-based average, cruise data, all trees measured |
| Silvicultural treatment | clear-cutting, shelterwood-cutting, single-selective-cutting, seed-tree-cutting, patch-cutting, retention-cutting, commercial thinning |
| Variables that influence the productivity | name |
| Effect on productivity | enhancing, diminishing, no significant effect |

## 3.3 Search Results

The search resulted in a total of 4574 hits (1335 records found on bibliographic databases, 3239 from search engines and online libraries). After the duplicate removal, 2960 results remained for the title and abstract screening (Figure 3.1). During this process, 2215 results were excluded. Of the remaining 745 results, 523 were retrieved in full text. After all titles and abstracts were filtered for the English language during the full-text screening process, an additional 62 results were excluded because of this language criterion. Out of the full-text reviewed results, 75 results that included studies of feller bunchers (67) or feller directors (8) were selected for data extraction. Figure 3.1 displays the progress from search to data extraction.

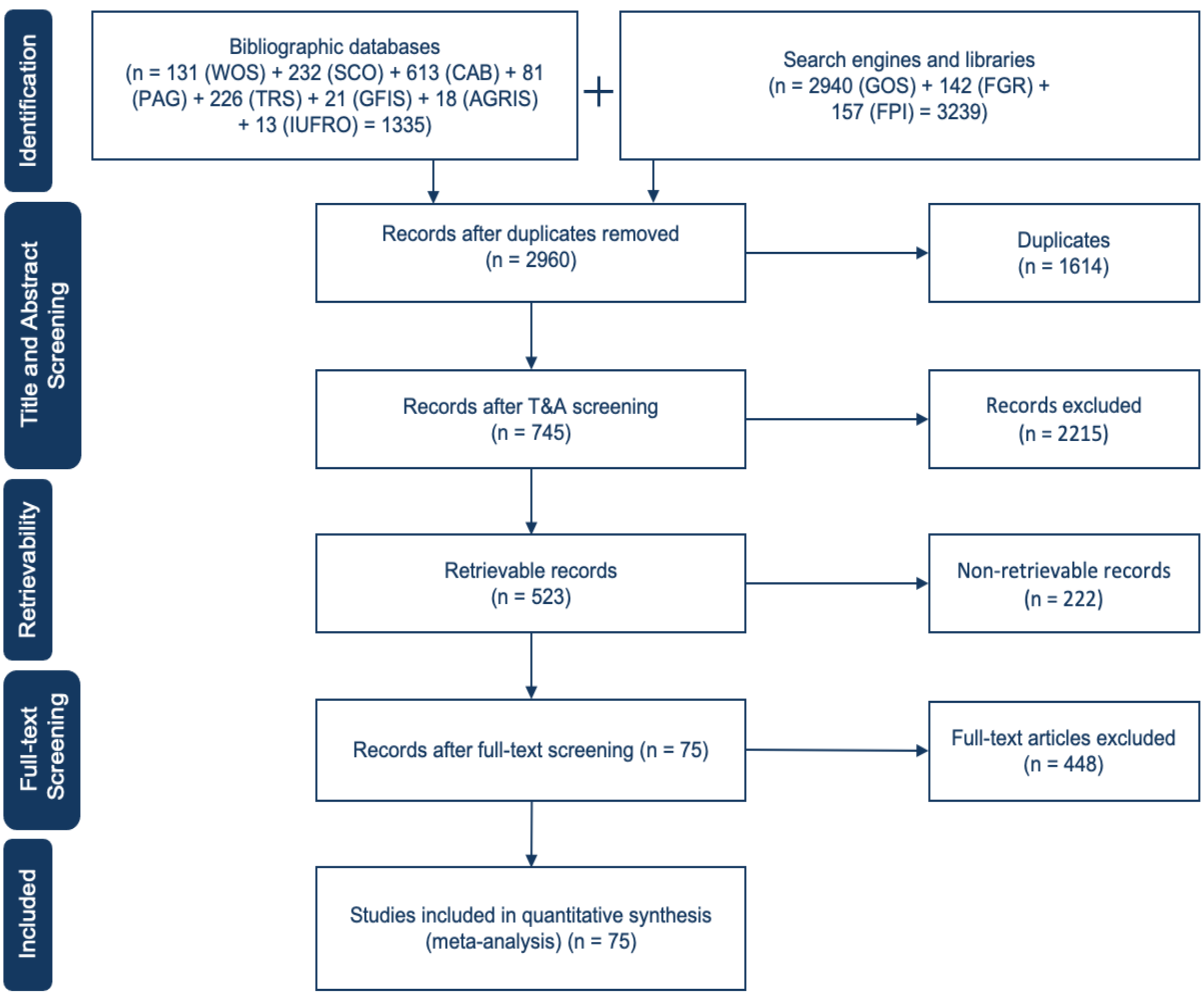


*Figure 3.1 Flow chart illustrating the number of results during different stages of the work process (adapted from Moher et al. (2009). n indicates the number of results remaining after each step of the work process.*

The selected results consisted of 19 peer-reviewed journal articles, six conference proceedings, one book chapter, and 49 technical reports. Of all results, 34 provided statistical analysis (e.g., ANOVA, Kruskal-Wallis test, linear regression). These included 17 of the peer-reviewed articles, four conference proceedings, one book chapter, and 12 technical reports

The geographical distribution of the results was relatively clustered. Most of the evidence on feller buncher productivity was gathered in North America (43 results Canadian research, 18 results US American research). Australia was counted in seven results as country of origin, three results were obtained from New Zealand, two from Italy, and one from Turkey. This distribution can be explained by the simple fact that most of the results were retrieved as technical reports from FPInnovations, which is a Canadian-based research institution. While this concentration could introduce a potential bias, FPInnovations is one of the primary sources for operational productivity studies in North America due to its long-standing research collaborations with industry and government. Out of the results that included research from Canada and the USA, 18 studies were conducted in the Pacific Northwest. Silversides and Sundberg (1988) did not specify the location of research.

In this study, search results were not excluded based on their publication date. Deliberately, no exclusion criterion was applied regarding the age of a study since there was no abrupt technological advancement in the development of the studied machines. The technology of these machines has been constantly evolving. Another reason for not applying an exclusion criterion is that outdated technology is still being used for timber harvesting in BC. Nevertheless, only four studies were published before 1995 (McMorland, 1985; Silversides and Sundberg, 1988; Richardson, 1989; Williams, 1990).

## 3.4 Productivity Influencing Factors

Productivity rates for feller bunchers and feller directors were reported in 60 and eight results, respectively. The remaining results reported productivity influencing factors without providing productivity rates. Out of the results that measured feller buncher productivity rates in volume/PMH (52), 90% reported productivity within a range of 9.6 to 150 $m^3$/PMH. Differences in reported productivity rates typically result from different harvesting conditions. Exceeding this range, productivity rates as high as 291 $m^3$/PMH were reported in five results (Andersson and Jukes, 1995; Andersson, 1997; Adebayo et al., 2007; Rittich, 2017b; Soman et al., 2020). It should be noted that these rates were reported for consistency in the systematic approach of this chapter. However, such high productivity rates seem unreliable and most likely stem from the inclusion of outliers in the studies' statistical analysis, erroneous data recording, or inaccurate inventory. These rates should have been questioned critically by the authors of these studies. Feller buncher productivity rates reported in mass/PMH ranged from 13 to 74.2 oven-dry tonnes/PMH. The results that included feller director studies reported a range of 7.3 to 88 $m^3$/PMH. This chapter, however, does not categorize or compare productivity rates, as the studies discussed were conducted in variable terrain, and for most, a combination of factors influenced the reported productivity. In order to directly compare individual factors among the results of several research studies, these factors need to be isolated. It is therefore essential to investigate individual factors in a controlled environment, which can be provided by machine simulators, for example (Ovaskainen et al., 2011). Additionally, PMH lacked a consistent definition across studies, and it was often unclear whether delays were included in the calculation. When delays were considered, the duration was sometimes not specified.

Factors reported to have affected productivity were categorized into site and stand-related and operation-related variables. Multiple factors directly related to each other were aggregated in groups. The relevance of factors and groups of factors was determined by how often they were mentioned in the results. With 59 total counts, site and stand-related factors were the most studied factors, while operation-related factors were studied in 49 of the results (Table 3.2).

Table 3.2 Factors that influenced feller buncher and feller director productivity mentioned in the resulst, categorized into site and stand-related, and operation-related, ordered by counts.

| **Productivity influencing factor** | **Counts feller buncher** | **Counts feller director** |
|---|---|---|
| Site and stand-related | | |
| Piece size | 27 | 3 |
| Ground slope | 7 | 2 |
| Obstructions | 5 | 3 |
| Species composition | 6 | - |
| Stand density | 3 | 2 |
| Operation-related | | |
| Silvicultural treatment | 14 | - |
| Harvesting intensity | 8 | - |
| Sorting | 6 | - |

Among all, eight of the results that investigated feller buncher operations (McMorland, 1985; Han and Renzie, 2001; Akay et al., 2004; Harrill and Han, 2012; Spinelli et al., 2013b, 2014; Dyson and Boswell, 2016; Roy and Rittich, 2017b) presented productivity rates without mentioning any influencing factors. In cases of multiple publications referring to the same results (Amishev and Evanson, 2010; Evanson and Amishev, 2010; Alam et al., 2013, 2014), the mentioned outcomes were only counted once.

### 3.4.1 Site and Stand-Related Factors

***Piece size***

Piece size is defined here as a group of factors referring to the volume of standing trees, volume of harvested logs, and standing tree diameters (DBH, cm). A value for piece size was reported in 60 results. However, not all of the results investigated its effect on productivity. In most of the results, an average tree or merchantable stem volume derived from cruise data, samples, or an average log size derived from data obtained during the processing of the logs, was used to determine productivity rates. While this chapter considered average piece sizes across studies, it is important to recognize that the uniformity of tree sizes within each study may have influenced the reported productivity rates. Studies with low variation in tree size likely provide more consistent productivity estimates, while those with high variability might include outliers or skewed results. The lack of reported SDs in most studies makes it difficult to quantify this effect, but future analyses should consider tree size distributions when interpreting productivity trends. In 20 of the results, it was not defined how productivity rates were obtained. Instead of using an average tree size achieved from cruise data or field samples to calculate productivity, Alam et al. (2013) improved the methodology by measuring each stem prior to felling.

To get a better understanding of the distribution of studies across different piece sizes, the results were grouped into size classes according to the average piece size reported. Since piece size was reported differently among the results, three categories were created to classify the studies. Several results reported multiple studies, each with different piece size classes. Every study with a reported piece size equals one count. Of the feller buncher studies that reported an average DBH, 79% were conducted in a range of 0 to 30 cm (Figure 3.2). Of the feller buncher studies that reported an average standing tree volume, 63% were conducted in stands with up to 0.60 $m^3$/tree (Figure 3.3). Of the feller buncher studies that reported an average harvested stem volume, 69% were conducted in stands with up to 0.60 $m^3$/stem (Figure 3.4). Reported feller director studies were conducted in stands with average DBHs ranging from 11 to 40 cm (Figure 3.2). Of the feller director studies that reported an average standing tree or harvest stem volume, 57% were conducted in stands with an average standing tree volume greater than 0.81 $m^3$/tree (Figure 3.3) and 80% in operations with an average harvested stem volume greater than 1.01 $m^3$/stem (Figure 3.4) respectively. The distribution of counts among the DBH, tree volume, and harvested stem volume indicates a lack of studies in the largest classes, especially for feller bunchers, which could be explained by a maximum felling-head diameter and more complicated felling techniques for larger diameter trees (Strandgard and Mitchell, 2010).

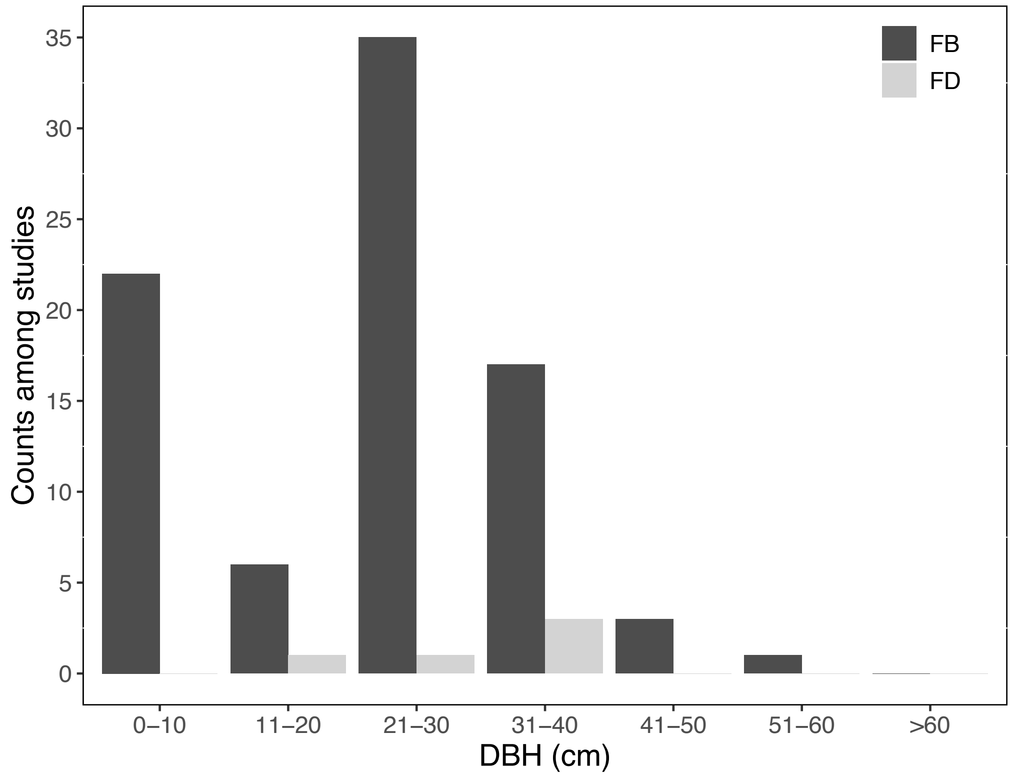


*Figure 3.2 Counts per DBH class for feller buncher (FB) and feller director (FD) studies.*

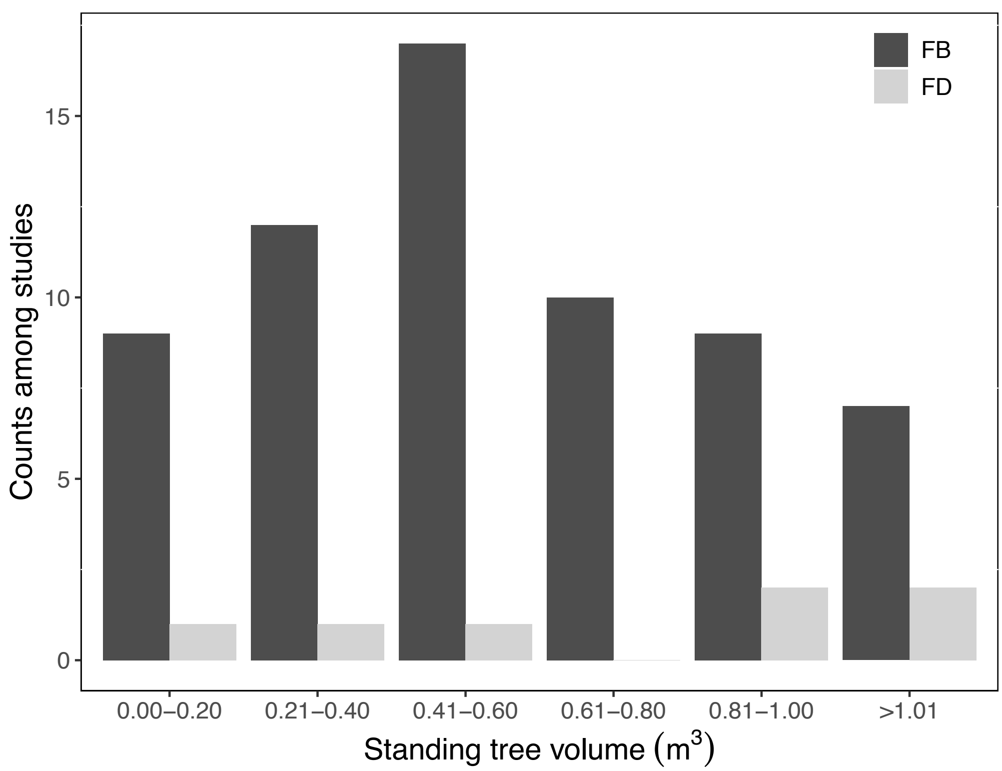


*Figure 3.3 Counts per tree volume class for feller buncher (FB) and feller director (FD) studies.*

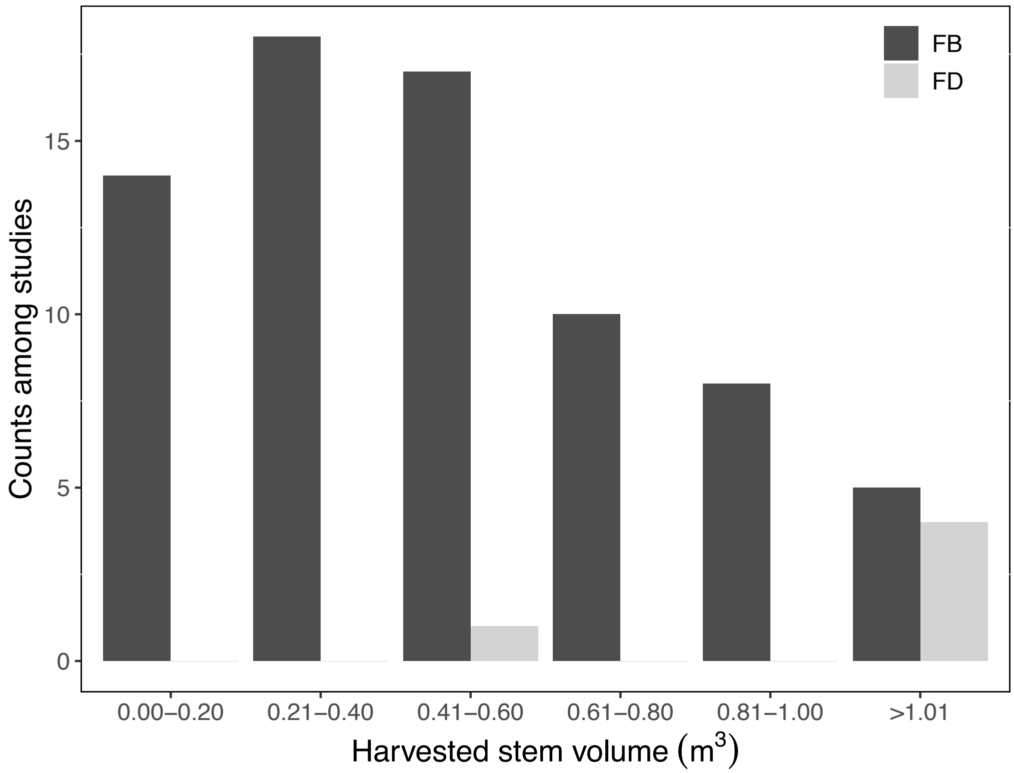


*Figure 3.4 Counts per harvested stem volume class for feller buncher (FB) and feller director (FD) studies.*

Nevertheless, piece size was by far the most studied factor influencing feller buncher and feller director productivity (30 counts in total). The harvested stem size (volume, $m^3$) was mentioned in 12 results (Meek, 1997, 2006; Phillips, 1997; McMorland, 2002; Hillman, 2003, 2004, 2005; Girard, 2009; Visser, 2009; Roy and Rittich, 2017c; Amishev and Dyson, 2018; Dyson and Strimbu, 2018), tree size (volume, $m^3$) was mentioned in nine results (Richardson, 1989; Andersson and Jukes, 1995; Andersson and Evans, 1996; Andersson, 1997; Strandgard and Mitchell, 2010; Lepage and Meek, 2011; Alam et al., 2013; Silversides and Sundberg, 1988; Ghaffariyan, 2019), and trees size (DBH, cm) was mentioned eight times among the results (Andersson and Jukes, 1995; Andersson, 1997; Long et al., 2002; Adebayo et al., 2007; Ghaffariyan and Acuna, 2012; Ghaffariyan et al., 2012; Hiesl et al., 2015; Soman et al., 2019). Long et al. (2002) were the only ones that mentioned merchantable tree height (m) as a significant productivity influencing factor.

Among all the results examining piece size, there is unanimity on a positive correlation between size (tree/stem volume, height, DBH) and machine productivity. These observations are in accordance with the "piece size law", which states the mechanical harvesting productivity increases at a decreasing rate with an increasing piece size (Visser, 2009). Richardson (1989) found that standing tree volume was the most important factor influencing not only the feller buncher but also the feller director productivity. Andersson and Evans (1996) reported that 79% of the variation in the productivity observed in elemental time and motion studies was explained by differences in the average volume per tree. Further, Meek (1997) stated that the harvested stem volume affects the productivity of mechanized harvesting more than the productivity of motor-manual harvesting. The study showed that an increasing stem volume decreased the travel and bunching time, as it was more challenging to accumulate enough small trees to an optimum bunch size for skidding. Strandgard and Mitchell (2010) reported a drop in the rate of productivity increase with increasing stem size, assuming that the flattening of the increase rate could be explained by a smaller number of stems per accumulation and the difficulty of handling stems of larger size. According to Visser (2009), in contrast to the "piece size law", there is a point at which the productivity of harvesting machines starts to decrease with increasing piece size. This machine-dependent "sweet-spot" projects the optimum piece size to achieve maximum productivity. Visser (2009) plotted the productivity rate over piece size for various harvesting operations with feller directors (mass 25-30 t) on gentle ground using an exponential regression and observed that the optimum piece size was 3.4 $m^3$/stem for the studied machines. His study was the only one to investigate optimum piece size for feller directors. Feller bunchers likely have a different optimal piece size because their felling heads are typically designed for smaller tree diameters, which limits their capacity. Additionally, feller buncher felling heads must support the weight of all accumulated trees, imposing a weight restriction that further constrains their capacity compared to directional felling heads.

***Ground slope***

The degree of ground slope can affect a felling machine's ability to travel. In 49 results, the ground slope, expressed as the slope percent, was mentioned for individual study sites. The average slope percent among the results was categorized into three slope classes based on travel abilities of conventional, specialized, and winch-assist machines (Plain to moderate slope 0 to 39%; Moderate steep slope 40 to 59%; Steep slope > 60%) (Figure 3.5). Most of the feller buncher studies (92%) were conducted on ground slopes from 0 to 39%. The distribution of feller director studies is relatively equal among the three classes.

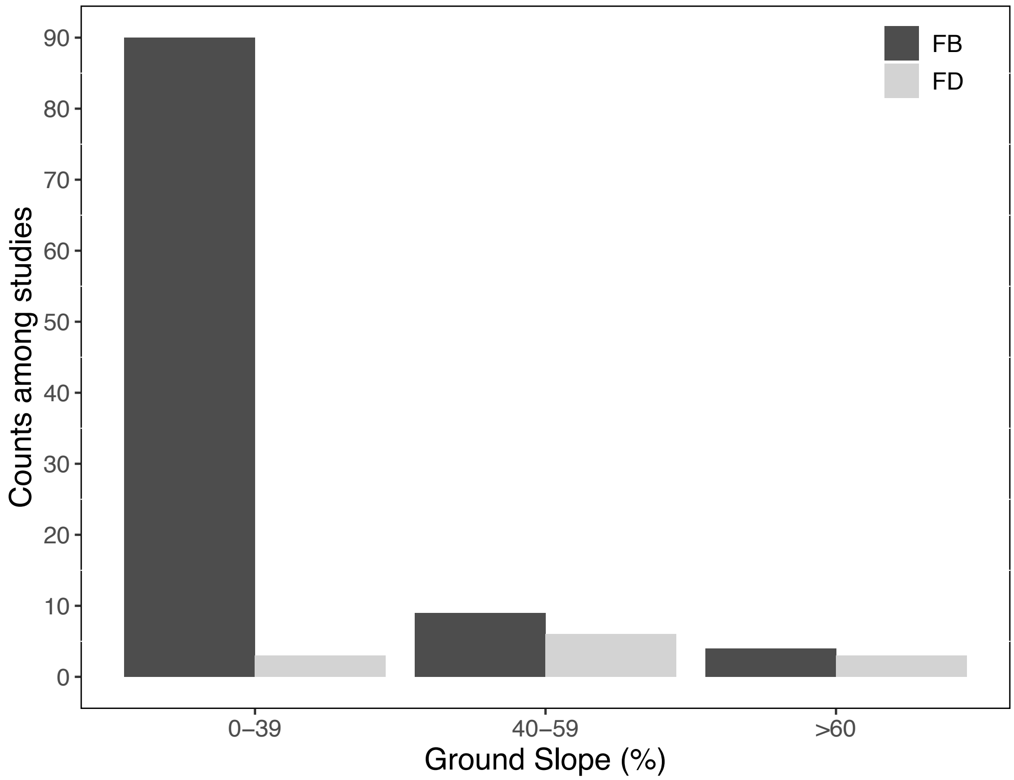


*Figure 3.5 Counts per slope class for feller buncher (FB) and feller director (FD) studies.*

Ground slope was the second most studied factor in the category of site and stand-related factors (nine counts). The degree to which ground slope affects machine productivity varies between the results. A decreasing effect was observed on moderate steep (40 to 59%) and steep slopes (> 60%) (McMorland, 2002, 2008; Kosicki and Dyson, 2003; Alam et al., 2013; Amishev et al., 2017; Amishev and Dyson, 2018; Dyson and Strimbu, 2018). Plain to moderate slopes (0 to 39%) did not seem to affect the productivity of feller bunchers (Watson et al., 1995; Hillman, 2001; Alam et al., 2013).

It is expected that the variable slope was difficult to isolate for most of the studies, which explains the variations in degree of influence reported for slope (Alam et al. 2013). To isolate the effect of slope better, Alam et al. (2013) analyzed the traveling and felling time of a feller buncher with a self-leveling cab based on digital terrain model derived from LiDAR data. The study was able to show an increase in time consumption for the two cycle elements, traveling and felling, with increasing slope percent. One of the explanations for this increase was a different technique used by the operator for felling and bunching on steeper slopes. The operator felled the trees while moving uphill on a plain to moderate slope, which is more comfortable for operators and increases productivity. On moderate steep slopes, the operator felled trees while moving downhill and bunched them while moving uphill again. A considerable amount of time was spent dragging the felled trees into areas where they were easy to extract.

Different winch-assist systems that included feller directors were investigated as well. Dyson and Strimbu (2018) and Leslie and Koszman (2019a, 2019b) studied the operations of a feller directors assisted by a winch mounted on a remotely operated bulldozer (ROB). Evanson and Amishev (2010) studied a prototype feller director with a winch mounted to the carrier. Amishev et al. (2017) studied a winch-assist system in which an excavator-based anchor machine was equipped with two winches and two parallel cables. All the mentioned results report the feasibility of these systems in moderate steep slopes to steep slopes. However, only Dyson and Strimbu (2018) stated a decrease in productivity on steep pitches with slopes percent between 80 to 85%. Only Amishev and Dyson (2018) and Leslie and Koszman (2019b) studied winch-assist harvesting systems that included feller bunchers.

***Obstructions and stand homogeneity***

Site and stand-related factors that potentially influence the machines' workflow or ability to travel were compiled in this section. Less-favorable terrain conditions such as uneven ground, ditches, boulders, small valleys, short abrupt slopes, snow, and downed trees are examples of these obstructions (Richardson, 1989; Meek, 1997; Dyson and Strimbu, 2018). In six of these results, productivity decreased with an increasing level of obstructions and stand heterogeneity. Gingras and Godin (1996), Kim (2017), and Han et al. (2018) reported a decrease in feller buncher productivity in the harvesting of blowdown timber compared to conventional operations. In Han et al. (2018), the feller buncher's cycle time increased by up to 56% when handling downed trees. The study investigated the effect of beetle-infested stands on productivity and concluded that the number of downed trees increases with the time passed after a beetle infestation due to windthrow, affecting the productivity of feller bunchers. McMorland (2008) reported a non-significant effect on productivity of stand conditions after beetle infestations. However, no information on the ratio of downed trees in the studied stands was provided. Meek (1997) reported a reduction in productivity of a feller buncher operating on relatively flat but unfavorable terrain when compared to operations on a moderate steep but even slope. The absence of ground obstacles appeared to favor the feller buncher's movement and thereby decreased moving time, leading to an increase in productivity. Terrain roughness was observed to have a decreasing effect on productivity by Richardson (1989), as obstacles that couldn't be climbed by the carrier increased the traveling time. Dyson and Strimbu (2018) reported that obstructions such as slash left on the ground from earlier felling operations had to be moved by the feller director, which increased the traveling time.

Only a small number of results reported snow cover during the studied feller buncher operations. The direct effect of snow cover on machine productivity was not studied in any of these results. However, Han and Renzie (2001) noticed that less than 50 cm snow cover did not influence the feller buncher's ability to cut the stems at a low position, close to the ground. On the contrary, Nishio (2010) reported a negative effect of snow cover, which decreased the productivity of the entire WT harvesting operation, without making observations for individual machines. In a study by Leslie and Koszman (2019a), the machine operator reported a decrease in traction while operating on snow. The operator further noticed that ice built up within the felling head which can potentially lead to mechanical issues due to a decrease in flexibility of hydraulic hoses.

***Species composition***

Previous studies have shown that tree characteristics affect the felling time of harvesting machines. For example, differences in the pattern of branch and crown growth might explain differences in the productivity of feller bunchers when harvesting coniferous and deciduous tree species (Dodson et al., 2006). The individual studies in the results of this chapter were categorized into four different types of species compositions (mixed-conifer, mixed-broadleaf, monoculture-conifer, monoculture-broadleaf) to highlight the abundance of studies in coniferous dominated stands (Figure 3.6). The most commonly mentioned species composition types in the results are mixed-conifer (58%) and mixed-broadleaf (26%). Operations in monoculture stands were studied less often (mono-conifers = 12%; mono-broadleaf = 4%). Species distribution was not provided in many of the results. A stand was considered mixed-species if there were more than one species listed. The number of monocultural or mixed-coniferous stands among the studies in the results might be explained by the geographical distribution of the results. Most of the studies were conducted in areas where coniferous species are dominant.

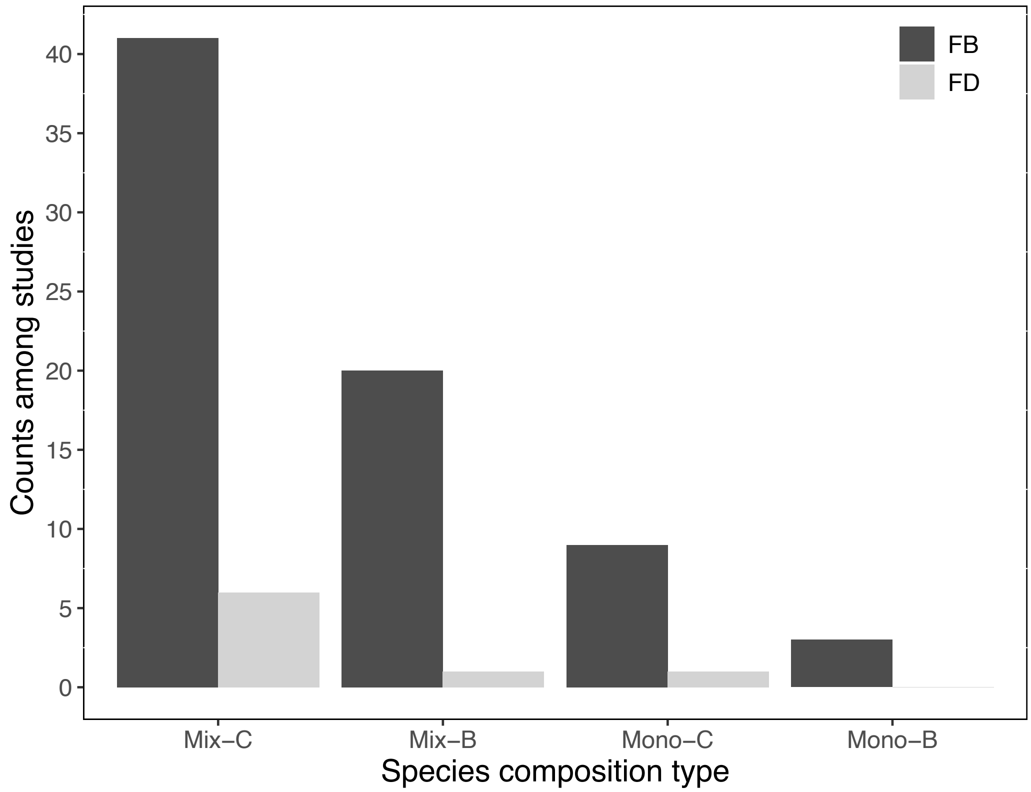


*Figure 3.6 Counts per species composition type for feller buncher (FB) and feller director (FD) studies. Mix-C = conifer-dominated stands containing mixed species (conifers or broadleaf trees); Mix-B = stands dominated by broadleaf trees. Stands in which only one tree species (conifer or broadleaf trees) occurred were considered monocultures (Mono-C; Mono-B).*

The effect of species composition was mentioned in six results with differences in its impact on feller buncher productivity. Four studies reported no significant effect of species composition on productivity (Williams, 1990; McMorland, 2008; Hiesl et al., 2015; Kizha and Han, 2016). Two studies reported an effect of species composition that either increased (Hillman 2005) or decreased productivity (Soman et al., 2020). Soman et al. (2020) reported an increasing effect of the variable "species" on delay-free cycle time in a hybrid tree-length operation. It was assumed in the study that the contrast in species characteristics between hardwood and softwood species affected the felling time. Hillman (2005) observed higher productivity for harvesting white birch (*Betula papyrifera* Marshall) when compared to harvesting coniferous trees of the same stem volume in the same stand. This difference was explained by the different dispersion of the two species over the cutblock that his studies were conducted in.

***Density***

Stand density and related factors (basal area, volume/ha), studied in five results, were grouped in this section. Three of the five results reported an increase in productivity with increasing stand density for both feller bunchers (Andersson and Evans, 1996; Long et al., 2002) and feller directors (Richardson, 1989). The remaining two studies reported no significant effect of stand density (Hiesl et al., 2015) or the basal area per hectare on feller buncher productivity (Meek, 2006). Increasing productivity has been linked by Andersson and Evans (1996) to an exponential increase in travel time with decreasing stand density. Hence, the effect of density was noticeable to a higher degree in less dense stands. Similarly, Richardson (1989) and Long et al. (2002) reported an increase of felling time with increasing distance between merchantable stems. Silversides and Sundberg (1988) support these findings with productivity equations that show an increase of productivity per PMH with an increase of volume per hectare. In contrast to this, Hiesl et al. (2015) found that neither stand density nor the basal area per hectare significantly affected feller buncher productivity. A linear-mixed effects model did not show explanatory differences in stands with unusually high densities, varying from 3211 to 5496 trees/ha, in a non-precommercial-thinned stand (Hiesl et al., 2015). Similarly, Meek (2006) found no significant relationship between any measured operating conditions, including the stand density.

### 3.4.2 Operation-Related Factors

***Silvicultural treatment and site preparation***

Among the operation-related factors, the effect of different silvicultural treatments on feller buncher productivity was studied the most. Compared to clearcuts, a decrease in productivity has been observed in single-tree or group selection cuts (Meek and Légère, 1998; Riopel et al., 2000; McMorland, 2002; Hillman, 2003; Sambo, 2003; Phillips, 2004; Sauder and Maclsaac, 2004; Girard, 2009; Vitorelo et al., 2011; Meek, 2013; Botard et al., 2015), while an increase in productivity was only found in one single-tree selection cut study (Nishio, 2010). However, no significant differences in productivity were found in partial cuts (Hartley and Han, 2007; Phillips, 2010). None of the results studied the effect of different silvicultural treatments on feller director productivity.

It was shown that the work cycle time is directly affected by the machine's maneuverability, which can be restricted in silvicultural treatments that protect individual stems (Riopel et al., 2000; Hillman, 2003; Phillips, 2004). The precaution with which the operators must maneuver their machines to avoid damaging residual trees increases travel time and thereby reduces the machine's productivity (Soman et al., 2020). In Soman et al. (2019), the differences in machine productivity between a clearcut and a selection cut operation decreased with an increasing mean harvested stem volume. This is supported by the findings of McMorland (2002), which showed that selection cut felling operations had a lower productivity when compared to clearcut operations under similar stand conditions (in terms of DBH and slope percent). Lowered productivity rates resulting from longer travel times in selection cuts were also shown by Meek and Légère (1998), Sambo (2003), Sauder and Maclsaac (2004), and Meek (2013). Nishio (2010) observed higher productivity in a selection cut treatment compared to a clearcut operation. However, the average stem size was much higher in the stand chosen for the selection cut treatment, which most likely explains these contradicting findings. Phillips (2010) observed increased cycle times in single-tree selection cuts when compared to both clearcut and group-selection operations. Due to insufficient data, the study did not find statistical significance in these differences.

To better understand the effect of site preparation on the cycle time of a feller buncher, Cormier (2002) studied spot scarification during felling. A prototype circular saw felling head was equipped with a toothed, hinged steel plate. The operator dragged the felling head along the ground while retracting the boom. On average, 14% of the cycle time was spent on this additional work element. When compared to conventional operations, the productivity of the machine decreased with higher degrees of spot densities, especially in stands with low harvest volumes.

***Harvesting intensity***

The harvesting intensity is very closely related to both the applied silvicultural treatment and the stand density. The intensity with which trees are felled can vary considerably between different treatments. In this study, the level of retention (Mcnamara et al., 1999; Phillips, 2004), removal volume (Hiesl et al., 2015), distance between harvested trees (Long et al., 2002; Girard, 2009; Vitorelo et al., 2011; Soman et al., 2020), and basal area harvested (Meek 2006) were aggregated as harvesting intensity related factors. Girard (2009) stated that the productivity of feller bunchers was higher in a clearcut than in a selection cut at equal harvested stem volumes. This was explained by an increase in travel time between trees to be felled. Similar to the effect of stand density in a clearcut operation, productivity decreases with a greater distance between selected trees. Soman et al. (2020) found that felling productivity was inversely proportional to the distance between harvested trees. Several studies reported decreasing productivity with an increasing level of retention in the selection cut treatments, which can also be explained by an increase in maneuver and travel time (Mcnamara et al., 1999; Phillips, 2004; Meek, 2013). On the contrary, Meek (2006) reported no significant effect of the harvested basal area on productivity in a comparison of several single-tree selection cuts. Hiesl et al. (2015) compared thinning operations with different removal intensities. The study concluded that removed volume per hectare did not significantly influence the feller buncher productivity. Rather, it was suggested that advantages in technology, highly skilled operators, and marking of crop trees prior to harvesting influenced the results.

***Sorting***

In a conventional WT system, the felled trees are extracted to the landing area, where they are processed and sorted by a processor. The six results that included studies of alternative sorting approaches and their effect on machine productivity are discussed in this section. Gingras and Godin (2001) compared conventional sorting at the landing with pre-sorting by species at the stump. The study observed that feller buncher productivity was decreased by 9% in a harvesting operation in which the felled stems were sorted at the stump. This was explained by an increase in travel time between the stump and separate bunches for different species. In addition, the number of stems accumulated per cycle was reduced when separating species due to the even distribution of the species over the area. These results were supported by earlier studies that also evaluated the effect of sorting at the stump (Gingras and Godin, 1996; Gingras and Soucy, 1999). McMorland (2008) and Conrad et al. (2013) studied the effect of sorting multiple products on productivity. McMorland (2008) stated that there is a significant decrease in productivity when sorting one product compared to two. In contrast, no difference was shown between two compared to three products. Meek (1997) studied a method of partially delimbing and sorting deciduous trees in partial cuts. The additional element in the feller buncher's work cycle decreased its productivity when compared to operations in which the delimbing was done motor-manually. Kizha and Han (2016) did not observe a significant effect of pre-sorting the felled stems on the feller buncher's productivity.

***Operator skill***

Operator skill has been shown to influence productivity, as the training of the machine operator affects the way the machine is maneuvered (Richardson, 1989; Dyson and Strimbu, 2018). There were six results reporting a positive effect of the operator skill on machine productivity. Andersson (1997) observed differences between the productivity of trainees and experienced machine operators working on the same feller buncher under similar conditions. The less experienced operators lacked knowledge of how to efficiently use the accumulator when bunching trees. Moreover, the inexperienced operators showed difficulties in maneuvering the machines in challenging terrain conditions. A similar effect of the level of operator training was observed by Hillman (2003). Although there are no studies that specifically investigated the operator effect in steep slope harvesting, Amishev and Dyson (2017) noticed lower productivity in winch-assisted operations on a cutblock with an average slope of 80% compared to a cutblock with an average slope of 50%. One of the explanations for this observation was the great care and attention required of the machine operator to maintain good machine traction and stability. Since winch-assist operations do not have a long history in the Pacific Northwest, many operators are inexperienced in this technology. The productivity of winch-assisted machines is expected to increase with increasing operator experience (Dyson and Strimbu, 2018). Sauder and Maclsaac (2004) observed an increased productivity in both clearcuts and selection cuts after operators gained experience. In a first trial, none of the three studied operators had any experience felling in selection cut operations. As a result, productivity was low compared to a second trial in which the operators were more experienced with the harvesting treatment. In accordance with the previous findings, Meek (1997) stated that a felling technique better suited to the conditions would have increased the efficiency of the operator. Richardson (1989) reported a lack of operator skill contributing to a lower productivity rate of feller directors. In the study, less skilled operators had more difficulty cutting and maneuvering around unmerchantable trees. The felling technique with these machines is, in general, more advanced and requires additional training compared to feller buncher operations. Although the effects were not studied directly, Dyson and Strimbu (2018) suspected untrained operators to be the cause for a decreased productivity in winch-assisted feller director operation. When the operating angle of the feller director was not in lead with the anchor machine, its tractive assistance was decreased, which led to a decreased productivity. Roy and Rittich (2017) were not able to provide statistical evidence but suggested that a controlled experiment with equal conditions for every operator would have shown differences in their productivity depending on their experience.

***Trail layout***

The layout of skid trails in partial cuts can affect felling machine travel time and productivity. In theory, a narrow system of skid trails in thinning or single-tree selection operations allows the felling machine to harvest the residual strips while staying on the trail. In a wider trail-spacing, the machine is required to leave the trail to cut trees before bunching the stems aside the trail (Coup et al., 2008). Three studies aimed to investigate the effects of trail-spacing on productivity, however, no significant effect was found. Coupe et al. (2008) compared felling activities in an 18.3-meter trail spacing and a 12.2-meter trail spacing system. Feller buncher productivity was found to be higher in stands with wider trail spacing. The differences were not statistically significant and were not able to be explained by other variables. Similarly, Meek (1997) reported no significant effect of 33-meter trail spacing compared with a 13-meter trail spacing. Plamondon and Brais (2000) studied a system with fixed skid trails for extraction and the freedom for feller bunchers to leave these trails for felling on so-called “ghost trails”. Machine productivity in operations with ghost trails was compared to conventional operations, in which the same trails were used for felling and extracting the timber. The study concluded that there were no significant differences in productivity between feller bunchers operating in these two systems. Meek (2006) expected lower feller buncher productivity due to higher travel and maneuvering time in a 33-meter trail spacing operation compared to a conventional trail spacing. However, the results showed higher productivity in stands with wider trail spacing, for which no explanation was provided.

***Trees per felling cycle***

The number of trees per felling cycle is an operational factor that is exclusively influencing the productivity of feller bunchers. Unlike feller director heads, most feller bunchers have the ability to accumulate several trees in one work cycle before bunching them for extraction. An increasing effect of the number of trees per work cycle on productivity was reported in four results. In Andersson and Dyson (2005) and Vitorelo et al. (2011), the cycle time was affected by the number of trees felled per work cycle. An increase of productivity with an increasing number of felled stems per cycle was observed, indicating that felling more stems per cycle at a longer cycle time is more efficient than felling fewer stems at a shorter cycle time (Andersson and Dyson, 2005). Andersson and Dyson (2005) found four trees to be the optimum number of felled trees per cycle to achieve maximum productivity in a stand with an average DBH of 19.7 cm. Similar results were obtained by Soman et al. (2019), which showed that feller buncher productivity was directly proportional to the tree size (DBH, cm) and the number of trees cut per cycle. However, the optimum number of trees felled per cycle can vary across different stand conditions, silvicultural treatments, and machine specifications. Strandgard et al. (2015) studied feller buncher productivity for a stand with an average tree volume of 0.22 $m^3$ and found comparably low productivity compared to studies in similar conditions. These unexpected findings were explained by the smaller average number of stems accumulated per cycle (2.9) compared to reference studies. The machine used in the study was assumed to be underpowered, as it had difficulties handling and accumulating more trees per cycle.

***Machine maintenance and performance***

The improvement of machine maintenance or performance can influence productivity. Rittich (2017b) reported a positive effect from a hydraulic tune-up on feller buncher productivity. Several machine parts were checked and adjusted to factory specifications in the tune-up. The adjustments resulted in increased maneuverability of the machine, which contributed to an increased productivity and decreased fuel consumption. In a different study, Rittich (2017a) studied the effect of reducing the revolutions per minute of a feller buncher engine on performance. This reduction had a negative effect on the machine's productivity. Carrier travel speed and stability were mentioned by Richardson (1989) as feller director productivity influencing factors. However, there was no further explanation for this observation.

***Anchor set-up and relocation***

The anchor machine plays an important role in winch-assist harvesting operations. Currently, there is no agreement regarding the work cycle definition in productivity studies of such systems. The question arises whether specific tasks related to the anchor machine, such as moving the anchor, should be included in the productive time of the machine or not. Even though the anchors provide essential support as the felling machine moves across the slope, thereby enabling a safe and productive operation, Leslie and Koszman (2019a) suggest that the relocation of anchors should be non-productive time by strict definition. Meanwhile, Dyson and Strimbu (2018) argue that if defined as productive work time, the two work elements set-up time and anchor relocation have a substantial impact on measured productivity per PMH.

Further, Dyson and Strimbu (2018) found that the angle at which the felling machine travels to the anchor machine had an impact on the felling machine's traction. As a result, the feller director productivity decreased if the machine was not traveling in lead with the anchor machine.

## 3.5 Conclusion

With its systematic approach, this study allowed the extensive collection of evidence on the factors influencing the productivity of feller bunchers and feller directors. The authors acknowledge that due to the language constraint, relevant publications might have been neglected. Nevertheless, because of the scientific methodology followed, conclusions on the results can be drawn. This chapter shows that among all factors identified as having influence on the productivity of feller bunchers and feller directors, piece size is the most studied and most relevant. Despite an increase in cycle time, productivity seems to increase with increasing piece size. Given the mono-directional nature of most productivity functions, there is no upper limit for the effect of increasing piece size. Due to a lack of feller buncher studies in higher volume and DBH classes, it is vital to investigate whether the productivity increase from piece size is only limited by the size of the feller-head.

Silvicultural treatments can have a significant impact on the feller buncher productivity. The more machines travel and maneuver, the greater the cycle time, thereby lowering the productivity while other influencing factors remain constant. Selection cuts increase the travel time between trees to be harvested, just as a lower stand density does in clearcuts. Generally, for both feller bunchers and feller directors, it can be stated that productivity will decrease in a more complex system with higher demands on the operators' skills. That being said, an experienced operator that is familiar with the silvicultural treatment can still achieve relatively high productivity when compared to a less skilled operator.

This study revealed a lack of productivity research in steep slope harvesting operations. As suggested in previous studies, especially the inclusion of the soil's bearing capacity as a variable affecting productivity on steeper terrain is lacking. Feller buncher productivity decreases in moderate steep slopes and steep slopes. However, a decrease in productivity on steep slopes was not observed in winch-assist feller director operations. One of the major drawbacks of in-field observational productivity studies is the fact that individual variables can be difficult to isolate. Different factors might enhance or diminish the influence of others, when simultaneously present. The effect of slope, for example, might be dependent on the soil type and the operator skills (especially in winch-assist operations) to some extent. The piece size-dependent productivity "sweet-spot" might be reached earlier on steep slopes as the handling of larger diameter stems becomes more challenging.

Despite the numerous factors identified as affecting productivity, this study has shown that there are still many factors whose effect on productivity has not been sufficiently studied. Particularly, there has not been enough study on the effects of snow cover on productivity. Snow can affect the traction of the machine's undercarriage and further interfere with the functionality of the felling head. Alternately, the reduced soil impact and lowered travel restrictions provided by snow cover might increase productivity by reducing travel time. To better understand the impact of snow on machine productivity, further studies are required.

Similarly, the operator effect—another important factor influencing productivity—did not appear in the results included in this chapter. While it may not have been specifically studied for feller bunchers, previous research in cut-to-length (CTL) harvesting has demonstrated the significant impact of operator skill and behavior on machine productivity. It is reasonable to expect a similar magnitude of operator effect, warranting further investigation in future studies.

Even though Kellogg (1992) stated, "much is known about harvesting productivity and how harvesting and stand variables affect the operational efficiency of mechanized harvesting systems," there is still much that remains unknown. In fact, this chapter revealed a lack of statistical analysis in the majority of the reviewed results. Although several best practice guidelines exist that aim to standardize the methodology for time studies, they do not seem to be widely used for feller buncher and feller director productivity studies. In order to compare productivity rates across studies, a standardized study design for productivity measurement is crucial.

Further, an accurate method of tree-size measurement in WT harvesting is needed to improve productivity models. So far, there are no applications for feller buncher or feller director that measure the size or number of felled trees. In most of the results in this study, the average volume used to determine productivity was either based on a sample of representative trees or was estimated from cruise data.

### 3.5.1 Limitations

This study acknowledges several limitations that could impact the generalizability and applicability of its findings. Firstly, the included publications in this chapter did not consistently report standardized units, making it difficult to compare results directly. Additionally, inconsistent methodologies in data collection among studies and the lack of metric definitions or missing information in some studies further complicated direct comparisons between studies. Several studies reported questionably high productivity rates, which should be treated with caution. Another notable limitation is the subjectivity of certain reported factors, such as operator skill, which are challenging to measure accurately and consistently. This subjectivity reduces the meaningfulness of these factors if not properly measured and reported. These limitations highlight the need for more standardized, transparent, and comprehensive approaches in future research to enhance the reliability and comparability of productivity studies in forest operations.

### 3.5.2 Future Research

To better understand productivity influencing factors such as the effect of tree size and achieve updated productivity rates for WT harvesting machines, technological solutions must become available that record data at the same standard, as it is done in CTL harvesting. OBCs such as FPDat II data loggers need to be investigated to facilitate a reliable and robust solution for automated remote data collection. In future research, improved productivity algorithms could be used in benchmarking tools that can accurately predict the productivity of WT harvesting operations. These updated productivity models will further allow the optimization of harvesting operations, help identify bottlenecks, and support the development of best practices. The future research opportunities suggested from this chapter are partially addressed in the following chapters.

# Chapter 4 - Automated Production Time Analysis Using FPDat II Onboard Computers: A Validation Study Based on Whole-Tree Ground-Based Harvesting Operations

## 4.1 Background and Objectives

The previous chapter revealed the lack of solutions for automated data collection in WT harvesting productivity studies. As demonstrated in the introduction of this dissertation, reliable data collection with manufacturer-agnostic solutions is still challenging in WT harvesting. The utilized technology should be simple to install and should not need to be reconfigured before each operation/site. It should also be robust, survive harsh operating conditions, and produce reliable data (Strandgard and Mitchell, 2015). It should further work in remote location without cellphone reception. The earlier introduced FPDat II data logger meets all these criteria and promises to be an important part in the solution to automated production data recording in WT. As it has been used in many studies to record time metrics, the technology has proven its reliability. However, only Pellegrini et al. (2013) has ever investigated the accuracy of MultiDat data loggers, the predecessor of the FPDat II. Therefore, a detailed validation and analysis of this technology is needed.

This chapter aims to develop a protocol for the analysis and interpretation of ignition and motion data derived from FPDat II data loggers. The goals were to estimate work time and productive time, measure the error in the estimates through the comparison with extensive field observations, and detect approaches to minimize such errors. The presented research in this chapter is not limited to the validation of feller bunchers, as the functionality of the data loggers is universal and not machine specific. A larger data set collected from 11 observed machines, helped to increase the number of observation points.

## 4.2 Material and Methods

### 4.2.1 Study Sites and Machines

The study took place in eight different ordinary clear-cutting operations in the Cutblocks A to H, between June and November 2022. For detailed site and stand information, refer to Table 2.1 in the “Study sites description” section in Chapter 2.

A total of 11 different machines (FB1 to 4; GS1, 2; LL1 to 4; PR1) employed for WT ground-based felling, primary transport, processing, and loading were monitored in the study. For more detailed information on the machines refer to the "Machines description" section in Chapter 2.

### 4.2.2 Data Collection

For the data collection of this chapter, direct observations, video recordings, and remote data collection with FPDat II data loggers were applied as described in the "Data collection" section in Chapter 2. A significant portion of the observation time (84.8%) was dedicated to felling and primary transport operations, with felling accounting for 147.2 h distributed over 16 workdays of feller buncher operations, and primary transport accounting for 194.8 h across 18 workdays. Within primary transport, loading-forwarding (i.e., hoe-chucking log loaders) was covered for 64 h, spread over six workdays. Skidding operations, including grapple skidders and the supporting log loader decking machine, accounted for a total of 130.7 h of direct timing, 83.9 of which were for grapple skidders. In this case, the two skidders and the decking machine were working simultaneously as a system across four workdays, totaling 12 observed workdays. Processing and loading, together, accounted for 15.2% of the direct timing covered in the study, with a total of 61.1 h of observations over seven workdays. This comprised 27.8 h of a log loader loading trucks and 33.7 h of monitoring of the dangle head processor, processing and loading.

### 4.2.3 Data Processing and Analysis

The analysis in this chapter focused on estimating the work time and productive time of the monitored operations through the use of FPDat II ignition and motion data, quantifying the differences between these estimates and field-based observations, as well as identifying criteria and thresholds for minimizing the errors throughout a sensitivity analysis. A detailed timing of the operations was conducted by analyzing the in-field video recordings described in the Introduction. Adobe Premiere Pro® 2022 (version 22.5.0), a video editing software, was used to place markers along the video timeline at the end of each element allowing to calculate their exact duration. Subsequently, element-level time studies were conducted for all machines, using common work element definitions for each machine type, as described in various studies (Gillies, 2001; Long et al., 2002; Ghaffariyan et al., 2012; Spinelli et al., 2013a; Strandgard et al., 2014; Strimbu and MacDonald, 2014b; Kulak et al., 2017; Han et al., 2018; Soman et al., 2020). A summary of the definitions of work elements for all monitored machine types can be found in Appendix B. To simplify the analysis of diverse machine activities across different operational contexts, work elements were then grouped into three categories:

- relocating work tasks: moving, traveling empty, and traveling loaded, where the machines change their location, even if only by a short distance;
- stationary work tasks: felling, bunching, clearing, brushing, handling wood, processing, and miscellaneous activities, where the machines operate without changing location;
- delays: time periods when machines are not operational due to various factors.

Delays were defined as any operational, personal, or mechanical interruptions to productive elements longer than six seconds. Work time was defined as all relocating and stationary work tasks and measured as $PMH_0$, while productive time was assumed as work time plus delays of up to 15 minutes (min), measured as $PMH_{15}$.

The data recorded by the FPDat II units that were installed on the observed machines was analyzed through a 24-hour (midnight to midnight) time study based on machine ignition and motion status. To logically interpret the data proxies for moving and idling time were used in the time study. The combination of 'Recorder ON' and 'Motion OFF' (i.e., idling) was considered as delay time, 'Recorder ON' and 'Motion ON' (i.e., moving) was considered as work time. Overall, productive time was defined as the sum of work time and delay time up to 15 min ($PMH_{15}$). Although the basic concepts and assumptions for analyzing work and productive time using machine ignition and motion data seem to be straightforward, anecdotal evidence indicated that short working or ignition-off events within delays in the FPDat II data can significantly impact the estimations, especially for productive time. For example, a one-second 'Motion ON' event between two 14-minute delay events would lead to the inclusion of 28 min and one second (s) into productive time. Similarly, a one-second 'Recorder OFF' event between two 14-minute delay events would have the same impact. To address this issue, a sensitivity analysis was conducted to test different thresholds for conversion of short working events within delays (hereafter named Working-To-Delay or WTD) and short ignition-off events within delays (hereafter named Off-To-Delay or OTD) into delays. The aim was to identify the combination of settings that minimizes the error in the estimation of daily work time and productive time. OTD was defined as a binary parameter converting all 'Recorder OFF' events less than 3600 s into delays and was either included in the analysis or not (OTD set at zero seconds). WTD was set to values ranging from zero to 180 s in 15- second increments, leading to a total of 26 possible combinations of OTD and WTD. The outcomes of the sensitivity analysis were compared with the field data to detect various error metrics and identify the best-performing combination of thresholds that minimize such errors. The selected error metrics included the aggregated error (i.e., differences) in both absolute and percentage terms, the mean absolute error (MAE), the root mean square error (RMSE), and the coefficient of variation of the RMSE, CV(RMSE). All the error metrics were calculated using daily summaries of work time and productive time as observational units. The effect of the inclusion of OTD and WTD thresholds on the estimate errors of work time and productive time was tested through the use of linear mixed-effect models, where WTD or the interaction between OTD and WTD were set as fixed factors and the machine identification (ID) and machine type were set as the clustering random factors, with machine ID nested within machine type. In particular, the analysis focused on the differences in the estimated marginal means of work time and productive time errors between each of the combinations of selected OTD and WTD and the values recorded with no conversion of short moving and ignition-off events within delays into delay (i.e., OTD0/WTD0). The pairwise contrasts used the Bonferroni method for adjusting p-values to account for multiple comparisons. This statistical approach was applied instead of one-way and/or two-way ANOVA for the violation of the assumption of independence of the observations. In the productive time linear mixed-effect model, the equal-variance assumption was violated for the OTD factor, and hence a heteroscedastic model was specified to estimate different residual variances within each of the two OTD levels. Mixed-effects linear models were also used to investigate the relationship between work and productive time errors versus the duration of the observation time, relying on the same random factors described above for the impact of OTD and WTD on the error metrics. In this case, the goodness of fit of the regression was tested through the coefficient of determination ($R^2_{LR}$) defined by Magee (1990) and based on the likelihood ratio joint significance test. In all cases, the significance level of the statistical analysis was set at 0.05.

## 4.3 Results

### 4.3.1 Direct Timing Observations

The study covered a total of 403.1 h of direct timing, distributed over 41 workdays with a minimum observation time of three hours (Table 4.1). Productive time amounted to 354.9

$PMH_{15}$, with 18% being delays of less than 15 min, which reduced the actual work time to 291.2 $PMH_0$. The utilization rate for work time and productive time varied across different machine types, ranging from 66.3% to 80.3% and from 83% to 90.7% of the total observation time, respectively.

*Table 4.1 Summary of the observations and direct timing results.*

| **Machine type** | **Observed Machines (no.)** | **Observed workdays (no.)** | **Total time (H)** | **Work time ($PMH_0$)** | **Work time rate (%)** | **Productive time ($PMH_{15}$)** | **Productive time rate (%)** |
|---|---|---|---|---|---|---|---|
| Feller buncher | 4 | 16 | 147.2 | 118.2 | 80.3 | 133.5 | 90.7 |
| Grapple skidder | 2 | 8 | 86.9 | 59.4 | 68.4 | 72.1 | 83.0 |
| Log loader | 4 | 13 | 135.3 | 89.7 | 66.3 | 120.9 | 89.4 |
| Processor | 1 | 4 | 33.7 | 23.8 | 70.5 | 28.3 | 84.0 |
| All machines | 11 | 41 | 403.1 | 291.2 | 72.2 | 354.9 | 88.0 |

Overall, stationary elements accounted for 48. % of the total observed time, relocating elements for 23.7%, and delays for 27.8% (15.8% productive delays and 12% non-productive delays). However, the distribution of time elements changed among different machine types (Figure 4.1).

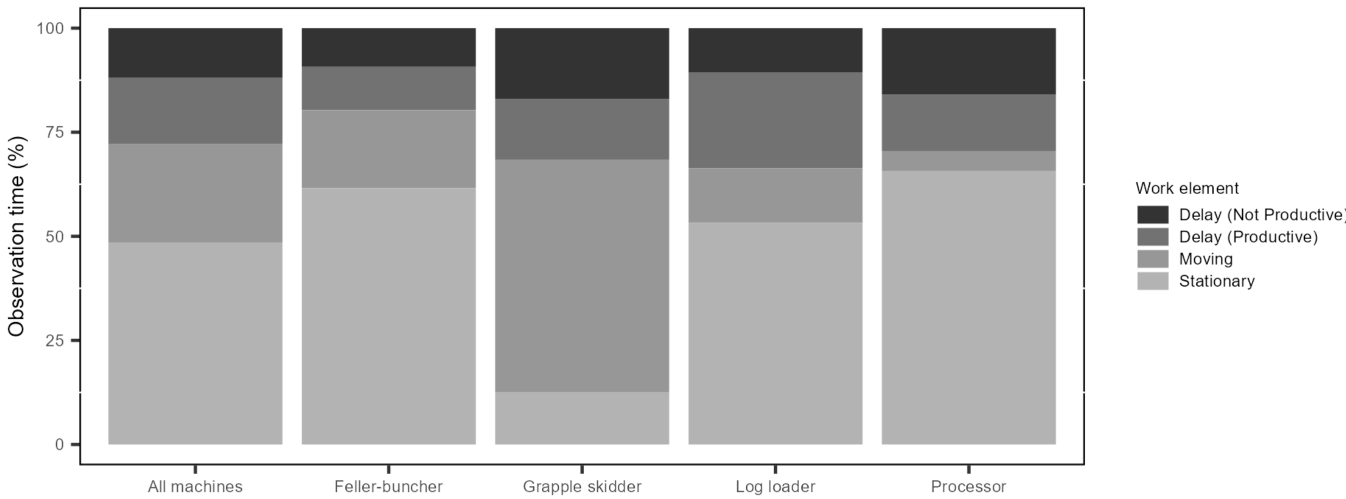


*Figure 4.1 Work element time distribution for all machines and by machine type.*

### 4.3.2 Work Time and Productive Time Errors With No Pre-Processing of FPDat II Data

With no conversion of short moving and ignition-off events within delays into delay (i.e., OTD0/WTD0), the overall work time error was 26.6 $PMH_0$ or 7.6% of the direct-timing work time. Daily summary results reported only positive work time errors, meaning that the work time estimated by the FPDat II data was always higher than what was recorded from direct timing. Almost all the observed days (40 out of 41) reported a work time error higher than 2%, while 15 workdays reported an error higher than 10%, reaching a maximum of 27.8% or 1.91 $PMH_0$ for log loaders. A significant portion of work time error variability was explained by the duration of the observation ($R^2_{LR}$ = 0.393, standard error (SE) = 0.0118, t-value = 5.17), with 0.061 $PMH_0$ increase in work time error per hour of observation. Work time estimated from FPDat II data showed an overall MAE of 0.65 $PMH_0$, a RMSE equal to 0.77 $PMH_0$, and a CV(RMSE) of 10.9%. These error metrics showed large variability among different machine types, with the MAE ranging from 0.30 to 1.02 $PMH_0$, the RMSE ranging from 0.36 to 1.12 $PMH_0$, and its CV ranging from 6% to 16.2% (Table 4.2).

*Table 4.2 Work time and productive time errors recorded with OTD and WTD set to zero seconds.*

| | **Work time error metrics** | | | | | **Productive time error metrics** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Machine type** | **Error [$PMH_0$]** | **Error [%]** | **MAE [$PMH_0$]** | **RSME [$PMH_0$]** | **CV(RSME) [%]** | **Error [$PMH_{15}$]** | **Error [%]** | **MAE [$PMH_{15}$]** | **RSME [$PMH_{15}$]** | **CV(RSME) [%]** |
| Feller buncher | 7.33 | 6.20 | 0.458 | 0.521 | 7.04 | 3.06 | 2.29 | 0.212 | 0.268 | 3.21 |
| Grapple skidder | 4.83 | 8.13 | 0.604 | 0.633 | 8.52 | 1.66 | 2.31 | 0.310 | 0.432 | 4.79 |
| Log loader | 13.25 | 14.8 | 1.019 | 1.120 | 16.23 | 1.12 | 0.92 | 0.206 | 0.237 | 2.55 |
| Processor | 1.20 | 5.03 | 0.299 | 0.356 | 6.00 | 1.75 | 6.16 | 0.437 | 0.460 | 6.49 |
| All machines | 26.61 | 9.14 | 0.649 | 0.771 | 10.85 | 7.59 | 2.14 | 0.249 | 0.329 | 3.71 |

The analysis of the work time error by time elements showed large positive errors for delays totaling at 29.3 $PMH_0$, with a MAE ranging from 0.47 to 1.14 $PMH_0$ and the RMSE ranging from 0.51 to 1.28 $PMH_0$ for the various machine types (note that no CV(RMSE) is calculable for delays, as their actual work time is zero by definition). Small negative errors were recorded for stationary and relocating elements, with a MAE and a RMSE lower than 0.19 $PMH_0$ and the CV(RMSE) ranging from 0.1% to 3.4% for different machine types. The analysis of productive time using the OTD0/WTD0 approach resulted in nine workdays (22%) with lower estimates than productive time recorded by direct timing, leading to a compensation of overestimation when the error estimates were aggregated over multiple days. Twenty-three monitored days (56.1%) reported productive time errors higher than 2% and two days showed errors higher than 10%, reaching a maximum of 11.5%. This reflected in 18 workdays with absolute errors higher than 15 min, and four days with errors higher than 30 min. No significant relationship was found between productive time error and the duration of the observation ($R^2_{LR}$ = 0.009, SE = 0.0159, t-value = 0.75). The MAE of productive time was 0.25 $PMH_{15}$, the RMSE equaled 0.32 $PMH_{15}$, and the CV(RMSE) was 3.7%. Separating the results by machine types, the MAE ranged from 0.21 to 0.44 $PMH_{15}$, the RMSE ranged from 0.24 to 0.43 $PMH_{15}$, and the CV(RMSE) ranged from 2.6% to 6.5% (Table 4.2). Similar to the work time analysis, delay-related productive time error metrics reported results comparable to those of the overall aggregated analysis, totaling 7.69 $PMH_{15}$. The MAE ranged from 0.21 to 0.44 $PMH_{15}$ while the RMSE ranged from 0.24 to 0.46 $PMH_{15}$. Consequently, the CV(RMSE) calculated for delay time in productive time estimates alone recorded significantly higher values than those for the overall analysis, ranging from 9.9% to 40.4%. In contrast, stationary and relocating work elements showed almost negligible errors in productive time estimates, with the MAE and the RMSE both lower than 0.01 $PMH_{15}$ and the CV(RMSE) lower than 0.18%.

### 4.3.3 Impact of Variation in WTD on Work Time Errors

Errors in estimating work time were unaffected by including OTD (Off-To-Delay) in the pre-processing of FPDat II data. By definition, transforming ignition-off time to delay time does not influence work time calculations. The sensitivity analysis on varying WTD values suggested a limited negative relationship between conversion thresholds and work time errors. Converting short moving events into delays reduced the overestimation of work time recorded by the FPDat II data loggers (Figure 4.2).

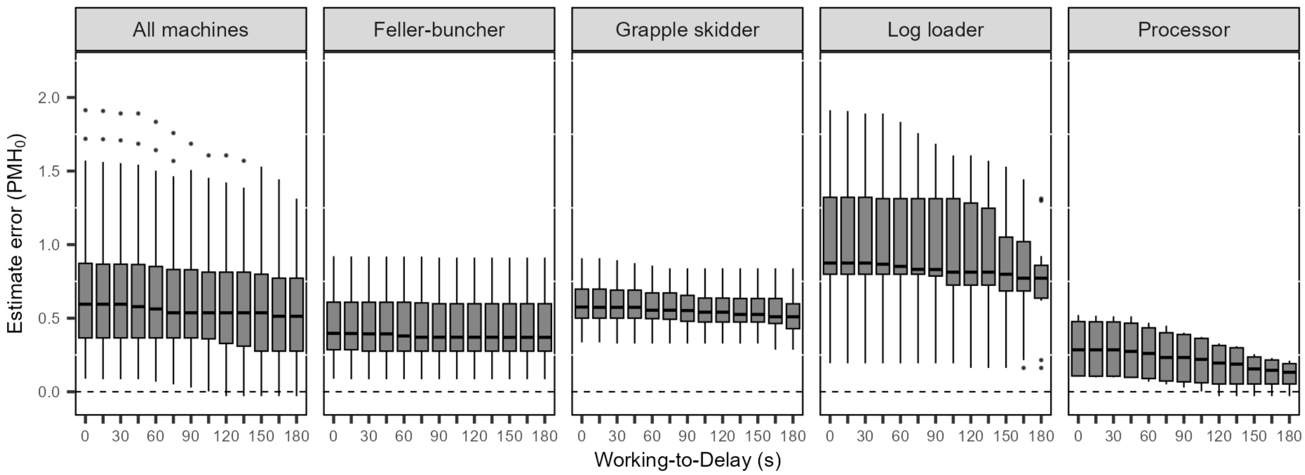


*Figure 4.2 Work time error recorded at different values of WTD for all machines and by machine type. Note that the values recorded with OTD set at zero seconds are excluded because identical and irrelevant.*

However, the application of a linear mixed-effect model, using WTD as the sole fixed factor, showed that the differences in Estimated Marginal Means of work time errors at various WTD values compared to values recorded with WTD set to zero seconds reached a maximum limited to 0.13 $PMH_0$ and did not differ significantly (p-values ranging from 1 to 0.050) (Figure 4.3).

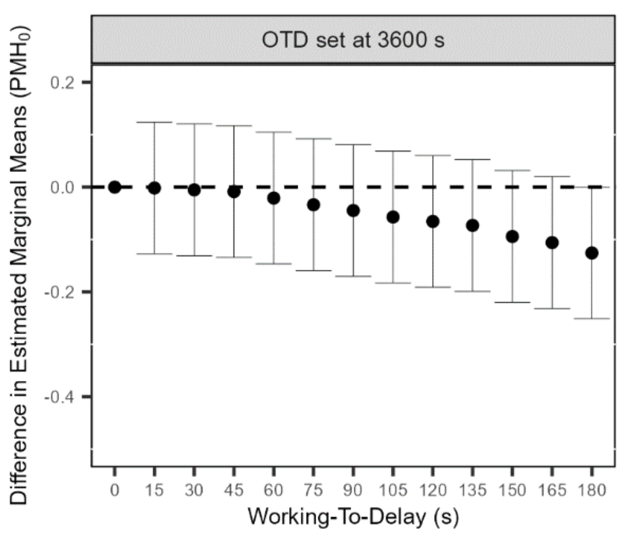


*Figure 4.3 Difference in Estimated Marginal Means of work time errors calculated by a linear mixed-effect model at different values of WTD compared to values recorded at WTD0. Error bars indicate the confidence intervals. Note that the values recorded with OTD set to zero seconds are excluded because identical and irrelevant.*

The limited impact of WTD on work time errors was also suggested by the trend of MAE, RMSE, and CV(RMSE) (Figure 4.4).

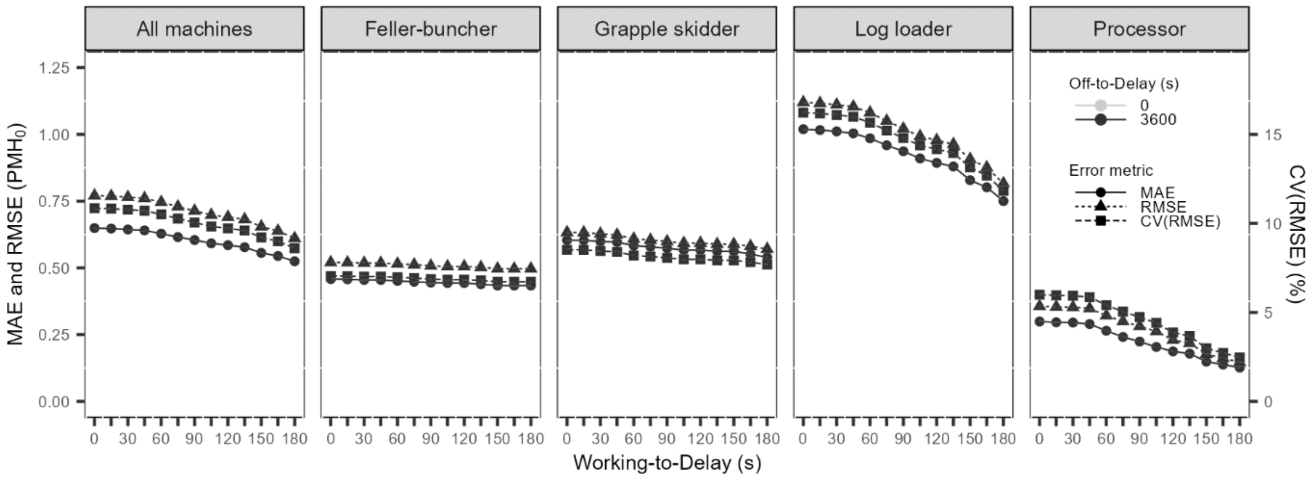


*Figure 4.4 Work time MAE, RMSE, and CV(RMSE) recorded at different values of WTD for all machines and by machine type.*

All the error metrics indicated a limited negative relationship, which was more pronounced for log loaders and processors with WTD values higher than 45 seconds. The lowest errors were observed at the highest WTD values. Compared to values recorded at OTD0/ WTD0, the error metrics indicated negative differences lower than 5.3% or 10.6% for feller bunchers and grapple skidders, respectively, but reached 27.1% and 58.9% for log loaders and the processor. A similar result was determined by analyzing the frequency with which a WTD value recorded the lowest error. In all machine types, the highest values of WTD (180 s) recorded the lowest work time errors in 100% of the observations. For feller bunchers only, all WTD values higher than 150 s reported the same effect.

At the elemental level, increasing WTD had only a limited impact on work time errors, with a tendency to reduce delay-related errors and increase negative errors of stationary and relocating work elements, recording the highest impact at the highest WTD values. Compared to values recorded with WTD set at zero seconds, maximum variations in delay-related MAE and RMSE were limited to 0.02 $PMH_0$ for feller bunchers and grapple skidders, and to 0.13 $PMH_0$ for log loaders and the processor. Almost all stationary and relocating work elements reported a maximum variation in MAE or RMSE limited to 0.06 $PMH_0$. The only notable exception was in stationary work elements for log loaders where the MAE increased by 0.14 $PMH_0$, the RMSE increased by 0.23 $PMH_0$, and the CV(RMSE) increased by 4.1 percentage points (pp) at the highest WTD values.

### 4.3.4 Impact of OTD and WTD Variations on Productive Time Errors

Similar to work time errors, productive time errors demonstrated a tendency towards a negative relationship with WTD for all machine types, becoming even more pronounced with the inclusion of OTD (Figure 4.5).

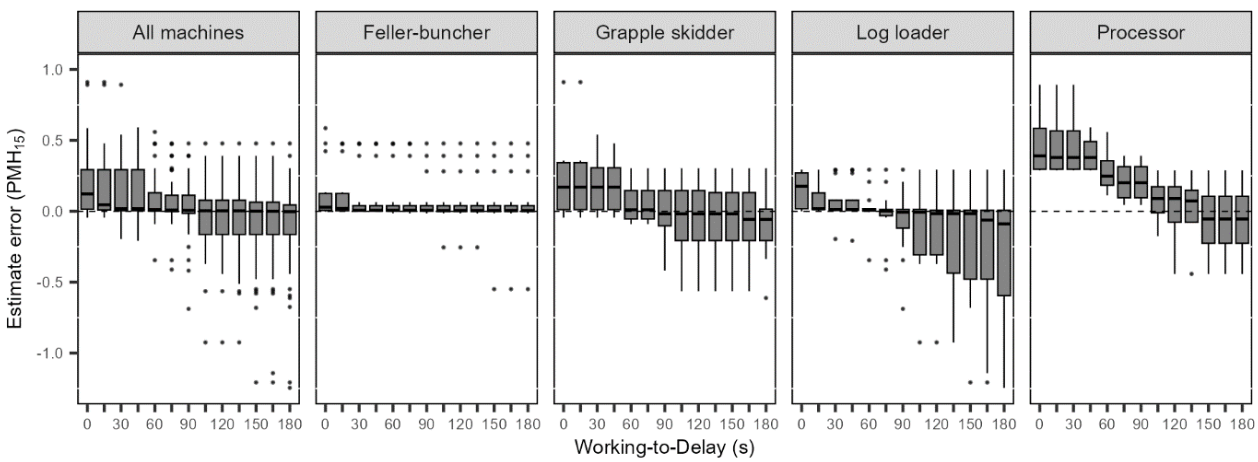


*Figure 4.5 Productive time error for different combinations of WTD values with OTD set at 3600 seconds for all machines and by machine type. Note that the values recorded with OTD set at zero seconds are omitted for graph clarity.*

In this case, the trends were clearer, and the impact was significant. The linear mixed-effect model analysis based on the interaction effect of OTD and WTD confirmed such trends, reporting significant differences (p-value < 0.05) in the Estimated Marginal Means of productive time errors recorded with WTD higher than 150 s or with inclusion of OTD and WTD higher than 105 s (Figure 4.6) compared to the values recorded with no conversion of short moving and ignition-off events within delays into delay (i.e., OTD0/WTD0).

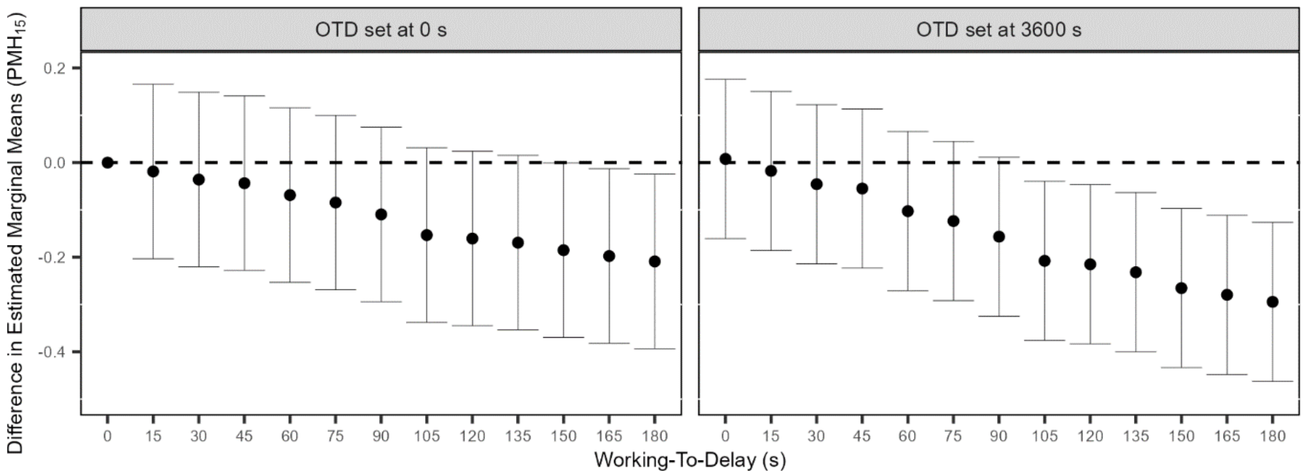


*Figure 4.6 Difference in Estimated Marginal Means of productive time errors calculated by a mixed-effect linear model at different values of OTD and WTD thresholds compared to values recorded OTD0/WTD0. Error bars indicate the confidence intervals.*

At the highest values of WTD (i.e., 180 s), the differences in Estimated Marginal Means reached -0.21 $PMH_{15}$ with inclusion of WTD only and -0.29 $PMH_{15}$ with the combined effect of OTD and WTD. Productive time MAE, RMSE, and CV(RMSE) measured for different machine types showed a similar trend with an offset between inclusion and exclusion of OTD and a typical reduction, or inflection point, towards central values of WTD, reaching the minimum between 60 and 105 s (Figure 4.7).

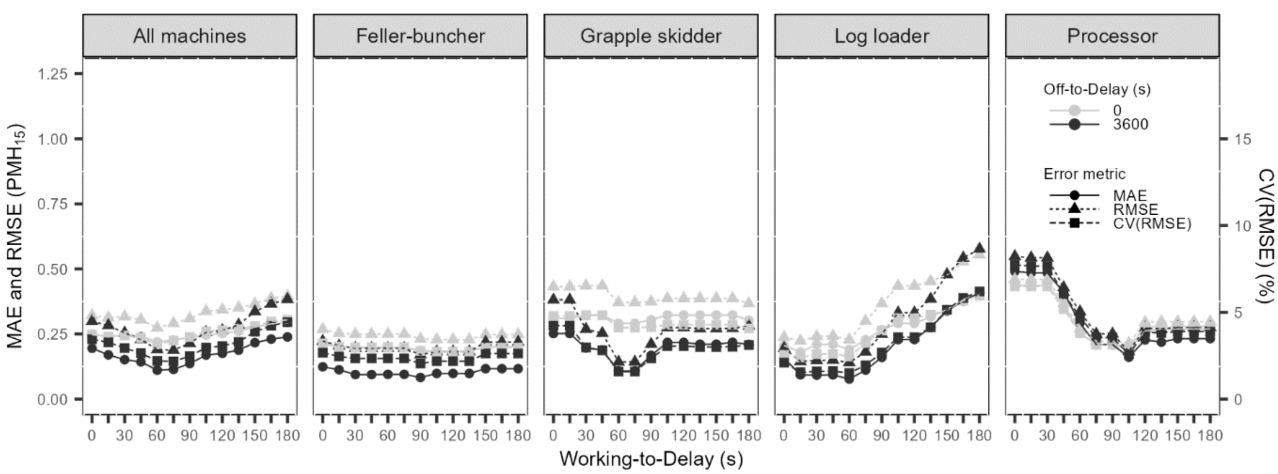


*Figure 4.7 Productive time MAE, RMSE, and CV(RMSE) recorded at different values of OTD and WTD.*

With full aggregation of the 41 daily values, all error metrics were minimized with the inclusion of OTD and WTD ranging between 60 and 75 s, depending on the metrics. Compared to values observed at OTD0/WTD0, the error metrics decreased by a minimum of 36.3% to a maximum of

67%. Similarly, the frequency analysis of threshold combinations that produced the lowest error (i.e., closest to zero) indicated the highest frequencies for the inclusion of OTD combined with WTD values between 30 and 90 s. Specifically, aggregating all 41 daily values with OTD and WTD set at 60 seconds resulted in the highest overall frequency (75.6%). The statistical analysis showed that the delay-related MAE, RMSE, and CV(RMSE) were smallest with the inclusion of OTD and WTD values ranging between 60 and 105 s. The same was observed for the overall daily values. Differences in MAE, RMSE and CV(RMSE) reached values of 0.27 $PMH_{15}$, 0.29 $PMH_{15}$, 23.8 pp respectively. On the other hand, differences in stationary and relocating MAE and RMSE were generally limited to a maximum of 0.03 $PMH_{15}$ and not operationally meaningful. The only relevant differences in the error metrics for stationary and relocating work elements were recorded for log loaders, were the increase in the errors at the highest WTD value reached 0.08 $PMH_{15}$ for MAE, 0.14 $PMH_{15}$ for RMSE, and 2.4 pp for CV(RMSE).

## 4.4 Discussion

This study represents the first attempt to develop, document, and extensively validate automated time analysis of a wide range of WT ground-based machinery based on data gathered through FPDat II data loggers. While this technology, in its various versions, has been used for over two decades, only one other validation study has been found in the literature. Covering more than 400 h of element-level direct timing through video analysis, this study provided a solid reference for the analysis of error metrics in work time and productive time estimation, filling a significant knowledge gap. The study also contributed to the advancement in the use of automated data gathering solutions in WT harvesting operations by providing evidence of error variations with inclusion of simple time thresholds for ignition and motion data processing. The remote data collection relied on the FPDat II data loggers only, without the integration of any tablet with the FPDat software on it for additional data input. Similar to the manual selection of pre-set buttons on MultiDATs, direct operator inputs into the tablet would have allowed to discriminate between different operators/shifts as well as identify activity/stop codes describing the reasons for delays or specific work tasks. Anecdotal evidence on the use of MultiDATs over the years, however, showed inconsistencies in stop code use and operator login procedures, and cannot be considered reliable on a large-scale monitoring, as also mentioned by Pellegrini et al. (2013). Therefore, relying only on the basic FPDat technology and automated data collection, a 24-hour based analysis has been selected, as no higher granularity (e.g., shift or cycle-level analysis) would be meaningful for a generalized automated time analysis of WT harvesting equipment. Although the study encompassed hundreds of hours of timber harvesting operations, relying on daily summaries as the observational unit for error analysis reduced the number of observations to 41. Another limitation of this approach arises when night shifts overlap the change of date, resulting in the shift being separated into two sections, aggregating the second section into the following day/shift. However, such events did not occur during the monitoring.

The work time and productive time estimations were based on the use of ignition and motion data with inclusion of time thresholds for pre-processing of the data. This solution provided an example of the capabilities to collect and estimate work time and productive time with a simple set of sensors. While the analysis focused on the FPDat II data loggers for their end-user readiness and popularity in the Canadian context, the same outcome could be achieved with any other solution relying on the same principles.

The time thresholds used in the analysis for pre-processing of the FPDat ignition and motion data included Off-To-Delay and Working-To-Delay. WTD thresholds, by definition, reduce the work time and productive time estimated by the FPDat II data. The inclusion of OTD does not have any impact on the estimation of work time, but can lead to either an increase or decrease of productive time. This variation depends on whether the aggregated delay events are shorter or longer than 15 min, determining if they are added to productive time. The analysis of work time and productive time errors included the observations of the differences between direct timing and the outcomes of different combinations of OTD and WTD threshold, as well as a summary of such differences into MAE, RMSE, and CV(RMSE) at various levels of aggregations. To avoid the impact of outliers, the frequency in which a combination of OTD and WTD reported the lowest error was also analyzed. This integration of various error metrics provided an overall picture that allowed the identification of errors of the FPDat II estimates, as well as the best combinations of time threshold that could be used to minimize such errors.

The exclusion of any time thresholds (i.e., OTD0/WTD0) provided a work time error, aggregated for the entire dataset, of 7.6% and a CV (RMSE) of 10.9%. Errors in work time were partially offset by variations in different work elements. However, larger overestimations during delays led to positive overall errors, resulting in an overestimation of work time. Work time errors were reduced with inclusion of WTD, but only at the highest values considered in the study. This is expected as the assumption that any motion event is part of a working activity (i.e., using moving time as proxy for work time) implies the inclusion of productive time tasks, as well as repairs and maintenance movements or other not-productive movements into work time, leading to an overestimation. Hence, the higher the threshold for the conversion of work time into delay, the higher the benefits in this study. For feller bunchers specifically, this trend appeared to be less pronounced, as indicated by the small difference in MAE related to delays of 0.02 $PMH_0$ between WTD0 and WTD values higher than 150. The differences in the impact of WTD inclusion across various machines can be explained by different work behaviors. Felling machines are typically in constant movement (both stationary and non-stationary) with little idle time, compared to log loaders used in loading operations, which involve a lot of waiting time, i.e., idle time. High threshold of WTD, however, still reported an overall error higher than 7.4% and CV(RMSE) greater than 8.6%.

Significantly, errors increased with the length of observation time. This trend is mainly due to numerous short delays throughout the day being mistakenly counted as work time, further aggravated by the system's default setting that requires a minimum delay duration of one minute to be recorded. These results are partially in contrast with what was reported by Pellegrini et al. (2013) who identified an underestimation of the aggregated work time measured on three pieces of equipment by MultiDATs, reaching a negative error 18.7%. Their observations, however, primarily focused on semi-mechanized cable skidder operations, where the machines had to stop for extended periods of time during the chocking of the logs. In that scenario, idling time, used as a proxy for delay time, encompassed both actual delays and work tasks that did not involve machine movements. The overestimation of work time, due to the concept of including any machine movement work time which was confirmed by the results of this study was not observed by Pellegrini et al. (2013). They reported a negative error of 5.5% in work time estimations from the solely monitored fully-mechanized grapple skidder. This contrast with the present results might be linked to different definitions of work time elements, approaches in the direct timing, work methods, data loggers and sensor, as well as calibration strategies and settings.

Productive time errors metrics indicated an overall error of 2.1% and a CV(RMSE) of 3.7% when excluding all time thresholds, demonstrating a default capacity of the FPDat II technology to estimate productive time with a reasonable error, meeting the standards of the FMC project collaborating industry partners. The lack of a correlation between the durations of the observations and the error in productive time estimates can be associated with the fact that major delays, subjected to the highest potential errors, are normally recorded at the beginning of the workday, during the initial idling for the warmup of the machine. Similarly, other significant delays are not evenly distributed throughout the workday; they tend to occur during specific, often unforeseen events, and their occurrence is independent of the observation duration. Significant benefits in the reduction of productive time errors were observed with the inclusion of OTD and WTD. The choice to include OTD into the analysis of FPDat data or similar technologies and principles should be driven by a conceptual point of view rather than its numeric effect. It is reasonable and recommended to consider short ignition-off events within the workday as delays, independently of their impact. The current OTD for including such events is one hour. The challenge, however, remains in determining when two 'Recorder ON' events should be treated as separate or combined into one, keeping in mind that most FPDat II data loggers do not record operator input or login data. In this decision-making process, it has to be noted that machine maintenance (with related ignition and motion input into the data collected by the FPDat II) is frequently carried out at night time after the end of the shift(s). If the OTD value is increased, the ignition-off time between the end of the shift and maintenance events could be converted into delays. While this can happen with a one-hour threshold, the likelihood increases with longer thresholds, affecting the reliable estimation of productive time. In all cases, the impact is restricted to the first and last delay before and after ignition-off events.

On top of the conceptual benefits, the inclusion of OTD typically provided a positive, even if limited, offsetting effect on the productive time error. With this inclusion minimal productive time errors for the metrics MAE, RMSE, CV(RMSE) were observed at WTD values ranging from 60 to 105 s, depending on the machine type. The combined analysis of aggregated error data and frequency analysis of minimum error recorded at different interactions of OTD and WTD supported the selection of WTD at 60 s as the most consistent value for the minimization of the productive time errors. With this selection of the best performing time thresholds (i.e., inclusion of OTD and WTD set at 60 s), the overall productive time error was reduced by 1.18 pp, reaching an overall value of 0.96%, MAE by 55.7%, RMSE by 41.3%, and CV(RMSE) by 1.53 pp. For feller bunchers, however, the inclusion of ODT and a WDT value of 90 s resulted in the smallest error metrics and should therefore be recommended as a standard for felling machines.

The impact of applying the same WDT on work time errors was noticeable but significantly less pronounced compared to its effect on productive time. The overall work time error was reduced by 0.29 pp, MAE and RMSE by 3.2%, and CV(RMSE) by 0.34 pp. The practical implication of such differences can be better understood when looking at an example of a machine with 2200 SMH per year, a standard productive time utilization of 80% (1760 $PMH_{15}$ $year^{-1}$), and a work time utilization of 65% (1430 $PMH_0$ $year^{-1}$). Without the inclusion of any OTD or WTD threshold, the automated analysis would have overestimated the yearly productive time by 37.6 $PMH_{15}$ and the yearly work time by 130.7 $PMH_0$. With the inclusion of OTD and WTD at 60 s the yearly productive time error would be reduced to 16.8 $PMH_{15}$ and the yearly work time error would be reduced to 126.5 $PMH_0$ $year^{-1}$. This means that while productive time measured by FPDat II data loggers (or similar technology) can be considered a solid and reliable metric, especially with inclusion of appropriate OTD and WTD thresholds, the errors in work time measurement are operationally impactful and unreliable. Even assuming the use of the work time recorded by FPDat data (with exclusion of all delays) to estimate productive time, the estimate would not be accurate and the error would be even higher (-10.5% error at OTD0/WTD0 or -10.7% at WTD 60 s), resulting in a minimum negative yearly error in estimation of productive time of 184.8 $PMH_{15}$.

Additionally, it is important to address the interpretation of production time results obtained from FPDat data or similar technologies. MultiDATs/FPDats data have been primarily employed for utilization estimates over medium to long-term monitoring, using the ignition input (‘Recorder ON’) as a proxy of SMH of the operations. None of the publications and technical reports relying on MultiDAT/FPDat OBCs specified or mentioned the inclusion of delays of up to 15 min, the reference used for productive or work time estimates, or any use of time thresholds for data pre-processing. Two main concerns arise from the missed information and use of the technology:

- the work time estimated by MultiDATs/FPDats can lead to significant errors and relying on work time only for productive time estimation can significantly and negatively compromise the accuracy of the outcome;

- the use of ignition ON data can represent a large underestimation of SMH and consequent overestimations of utilization as defined by international standards.

Because those two points are in direct contrast with each other (with consequent error compensation), the utilization values reported in such publications might be reasonable, but should be carefully considered. A more appropriate solution for productive time utilization analysis could be detecting productive time from OBCs, which has been demonstrated as a reliable metric, and relating it to known/assumed SMH, similar to the approach suggested by Harrill et al. (2018). That said, the ignition ON time recorded by OBCs, as well as the ratio of productive time and work time over the total ignition ON time, can provide useful metrics for production and performance monitoring, as was also pointed out by Strandgard et al. (2011). Finally, it is important to note that with the current technology, which relies solely on ignition and motion sensor thresholds, it is not only impossible to distinguish productive work tasks from non-productive machine movements, but also to differentiate between various work tasks. While this is typically not a problem for general estimation of productive time, it can become an issue in the case of versatile machines suitable for multi-purpose operations, including log loaders used for primary transport and loading, or processors used for processing and loading. In such instances, it would be beneficial to separate the different phases of the supply chain for proper monitoring and theoretical improvement, but further criteria, sensors, and/or data capturing technologies must be integrated into the system.

## 4.5 Conclusion

In this chapter automated time analysis protocols for a range of fully-mechanized, WT ground-based forestry equipment were developed, errors in the estimates time metrics were identified, and strategies to minimize such errors were developed. The automated time study approach utilized machine ignition and motion data from FPDat II data loggers and applied time thresholds for data pre-processing, for daily production time analysis. The repeatability of this approach across other solutions based on the same or similar principles makes it universally applicable to any ground-based forest machine. While the results revealed limitations in the approach to accurately identify direct work time ($PMH_0$), the approach successfully estimated productive time ($PMH_{15}$) with an aggregated error lower than 1%, suggesting the inclusion of WTD and OTD thresholds for productive time analysis based on data logger ignition and motion data. This positive outcome promotes the opportunity to further develop the automated production time analysis and integrate it with solutions for the identification of daily area covered by the monitored machines. The use of zonal statistics and extrapolation of volume information on area covered could allow for the estimation of daily production data to be integrated with productive time measurements for productivity analysis. Such an approach can potentially lead to close-to-real-time automated production performance analyses, continuous monitoring of timber harvesting progress, as well as extended data collection for benchmarking, logging rate predictions, logistics, as well as tactical and strategic planning.

# Chapter 5 - Preliminary Validation of Automated Production Analysis of Feller Buncher Operations: Integration of Onboard Computer Data with LiDAR Inventory

## 5.1 Background and Objectives

The FPDat II OBC system provides a robust and reliable solution for automated production data collection. As discussed in Chapter 4, estimates of productive time for felling machines show minimal errors. However, time measurement alone is insufficient for determining machine productivity rates - the missing component is volume, which FPDat II cannot measure. This challenge of unmeasured volume in WT harvesting persists until processing at the roadside.

Like many OBCs, FPDat II data loggers have GNSS receivers that provide time-stamped machine position data, allowing for the reconstruction of machine paths. In clear-cut operations, felling machines can be assumed to remove the standing volume within their travel area (excluding previously felled areas and roads). Thus, the area covered can be linked to the volume of standing timber.

While this approach is conceptually simple, limitations arise from the frequency at which GNSS points are recorded by the data loggers. The default thresholds of 25 meters of distance or 60 minutes of time, which must be exceeded to trigger a new point recording, introduce potential inaccuracies. Simply recreating the machine's path between these points will likely underestimate the area traversed, requiring buffer applications that exceed the machine's reach to estimate the actual area covered based on GNSS data. Once the area covered is estimated, zonal statistics on inventory data can retrieve the corresponding volume information.

This chapter develops a protocol for automated production analysis of feller bunchers, the primary felling machine in BC identified in Chapter 3, by integrating FPDat II machine time and location data with inventory data. To quantify the errors in the estimated production metrics (productive time, area covered, volume harvested and derived productivity), a preliminary validation of the protocol was carried out on feller buncher operations in direct comparison with conventional in-field data collection. This validation is essential for demonstrating the feasibility of integrating OBC information with inventory data.

## 5.2 Material and Methods

### 5.2.1 Study Sites and Machines

Three in-field studies were conducted to collect detailed production time and daily area covered information of feller buncher clearcut operations in cutblocks A, C, and D. The cutblocks were located in the interior of the province (A: 110 km northwest of Fort St. James) and across the coastal forests on Vancouver Island (C: 8 km southwest of Parksville; D: 8 km north of Lake Cowichan). For detailed site and stand information, refer to Table 2.1 in the "Study sites description" section in Chapter 2.

The three feller bunchers (FB1, FB2, and FB3) were monitored during the in-field observation, covering a total of 14.3 ha, which only represented a portion of the three cutblocks. All monitored feller bunchers were of similar size (Table 5.1) operating in a variety of WT ground-based harvesting systems that included either skidders (cutblock A) or loader-forwarders (cutblocks C and D) for primary transportation. In cutblock A, two feller bunchers with tilt cabins of identical make and model were working in close proximity to each other (FB1 and FB4). Due to video data loss, FB4 was only included in the sensitivity analysis of this chapter to determine the best criteria for automated area covered estimations. In cutblock C, a single feller buncher (FB2) was monitored. FB3, a tilt cabin feller buncher, was monitored in cutblock D, working in close proximity to a second feller buncher (not equipped with FPDat II unit) and a feller director (FD2W) on steep terrain. All of the operators involved in the study had at least 10 years of experience.

*Table 5.1 Machine specifications of the observed feller bunchers FB1, FB2, FB3, and FB4 and their attachments.*

| **Machine specifications** | **FB1 & FB4** | **FB2** | **FB3** |
|---|---|---|---|
| Mass (kg) | 33 565 | 35 600 | 37 760 |
| Max. reach (m) | 8.46 | 8.46 | 8.9 |
| Min. reach (m) | 4.8 | 4.8 | 4.9 |
| Engine power (kW) | 243 | 224 | 243 |
| Track width (m) | 0.61 | 0.70 | 0.61 |
| Track length (m) | 4.75 | 4.75 | 3.8 |
| **Felling head specifications** | | | |
| Mass (kg) | 2950 | 2950 | 3140 |
| Circular saw max. cut diameter (m) | 0.66 | 0.66 | 0.55 |

### 5.2.2 Data Collection

The data collection for this study included GNSS tracking, video recording, remote tracking and direct observation of the monitored machines and cutblocks. For a detailed description of the applied methods please refer to the "Data collection" section in Chapter 2.

The cumulative duration of direct observations amounted to 106.3 hours, spanning 10 days across the three cutblocks. Specifically, cutblock A accounted for 47 hours over four days, cutblock C accounted for 38.6 hours across four days, and cutblock D accounted for 20.7 hours over two days.

### 5.2.3 Data Analysis

A detailed time study was done by observing and post-processing recorded videos. Similar to the data analysis in Chapter 4, Adobe Premiere Pro® 2022 (version 22.5.0) was used to distinguish between different work elements and determine their durations. This study distinguished between felling, bunching, clearing, moving, and all delays (including personal, operational, or mechanical) greater than 6 seconds (Appendix B). A whole work cycle consisted of at least a felling and a bunching element, but could include all other elements. The detailed time study at element-level allowed for the accurate quantification of productive time (measured as $PMH_{15}$), consisting of delay-free work time (measured as $PMH_0$) and delays up to 15 minutes. As discussed in Chapter 4, the FPDat II units cannot distinguish between two shifts during the same day without manual operator input (login). Therefore, all information was aggregated at the day-level for individual observations and then compiled to provide a comprehensive overview for each machine, referred to as the machine-level in this study.

The drone-captured images were processed into georeferenced orthomosaic images with a resolution of approximately 4 cm per pixel and an expected error range of 0.07 to 0.3 m (Ludwig et al., 2020), utilizing the software Agisoft Metashape (version 2.0.1). Importing the images into QGIS (version 3.32.0-Lima), a GIS software, enabled the manual delineation of polygons to visually represent and quantify the daily advancement of work. As a result, the precise area covered during each work shift was accurately identified and expressed in hectares. Additionally, a script was developed in Python and subsequently executed within the QGIS environment to compute zonal statistics of stand and site attributes. LiDAR-based inventory data and digital elevation models were available in the form of GIS layers with a minimum of 20-meter and one-meter resolutions, respectively. Based on these layers, the total and mean net merchantable volume harvested and net merchantable volume per ha were calculated for each daily area covered. To mitigate inaccuracies in potentially outdated forest inventories during productivity calculations, the industry collaborators provided the scaled merchantable volume under bark for all observed cutblocks. This volume is measured at the sort yard or sawmill according to standards described in the BC Scaling Manual in which the required accuracy for weight scale sampling is set as ±1% at the 95% confidence interval (CI) (British Columbia Ministry of Forests 2021). This volume was distributed across each cutblock according to the volume density information from the LiDAR-based inventory.

The remotely collected FPDat II raw data were downloaded from the cloud server post operation for subsequent analysis. An automated time study was conducted utilizing the ignition and motion data following the methodology introduced in Chapter 4 (Figure 5.1). Subsequently, productive time was calculated consisting of work time and delays up to 15 minutes ($PMH_{15}$).

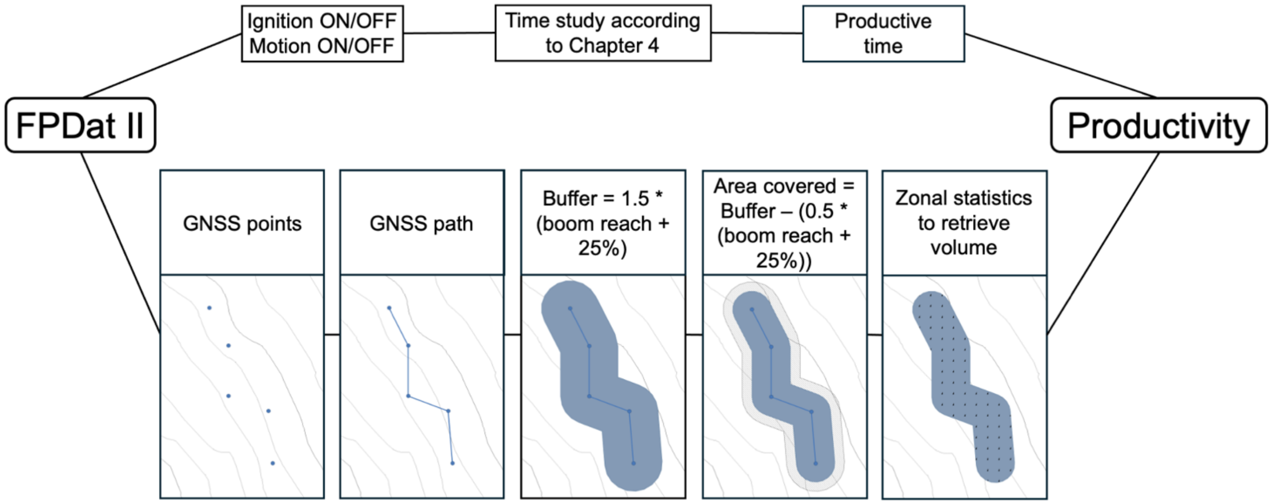


*Figure 5.1 Flowchart of the introduced protocol for automated production analysis of FPDat II data with detailed description of the individual steps of area covered estimation based on GNSS raw data.*

To automatically estimate the daily areas covered, polylines were created between consecutive FPDat II GNSS points to recreate the path travelled by each machine. Assuming that the machines worked within their boom reach, a buffer equal to boom reach applied to the machine path should recreate the area covered. However, due to the relatively low recording frequency of location data by the OBC, these paths can misrepresent the actual machine path. Therefore, an appropriate buffer size and application needed to be defined to close gaps of actual area covered not captured by the machine path. Two different components were chosen to determine the buffer: machine reach and the factor with which the buffer is applied. Machine reach was defined as the increase in boom reach size up to 100%. The factor defined the multiplier with which the machine reach was applied to the machine track and subsequently was subtracted from the generated polygon to the initial machine reach (e.g.: boom reach + 25%) to retrieve area covered (Figure 5.1). This approach of applying the buffer especially helped closing gaps within the area-covered polygons (Figure 5.2). A total of 25 combinations of machine reach (boom reach increased by 25%; 50%; 75%; and 100%) and factor (machine reach scaled up by 1; 1.5; 2; 2.5; and 3 times) were tested in a sensitivity analysis. This was done to determine the most accurate combination to estimate area covered with the lowest error at machine- and day-level. By default, the estimated area a machine covered was restricted to the boundaries of the cutblock. Furthermore, an area was only attributed to the first machine that covered it - if the same or a different machine crossed that area on a subsequent day, this was not considered as additional area covered. In situations where two machines covered the same area on the same day, the area was allocated alphabetically by machine name.

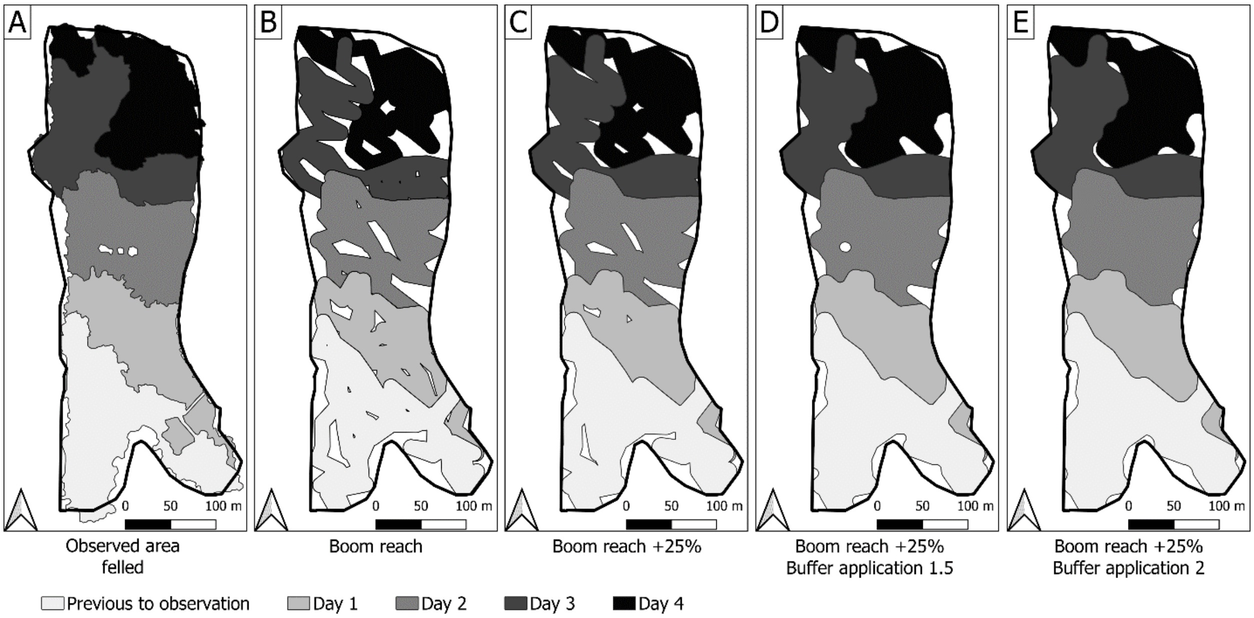


*Figure 5.2 Different combinations of machine reach and buffer application to delineate area covered from GNSS machine tracks in comparison. A: area covered during observation, B: machine reach = boom reach, C: machine reach = boom reach + 25%, D: machine reach = boom reach + 25% and buffer application = 1.5, E: machine reach = boom reach + 25% and buffer application = 2.*

To accurately assess the effectiveness of the automated FPDat II data analysis in detecting actual area covered, a direct comparison of observed and estimated area was conducted, focusing on 'positive' differences (areas detected by the system that were not actually felled), 'negative' differences (areas that were felled but not detected by the system), and the overlap between the observed and estimated areas (Figure 5.3).

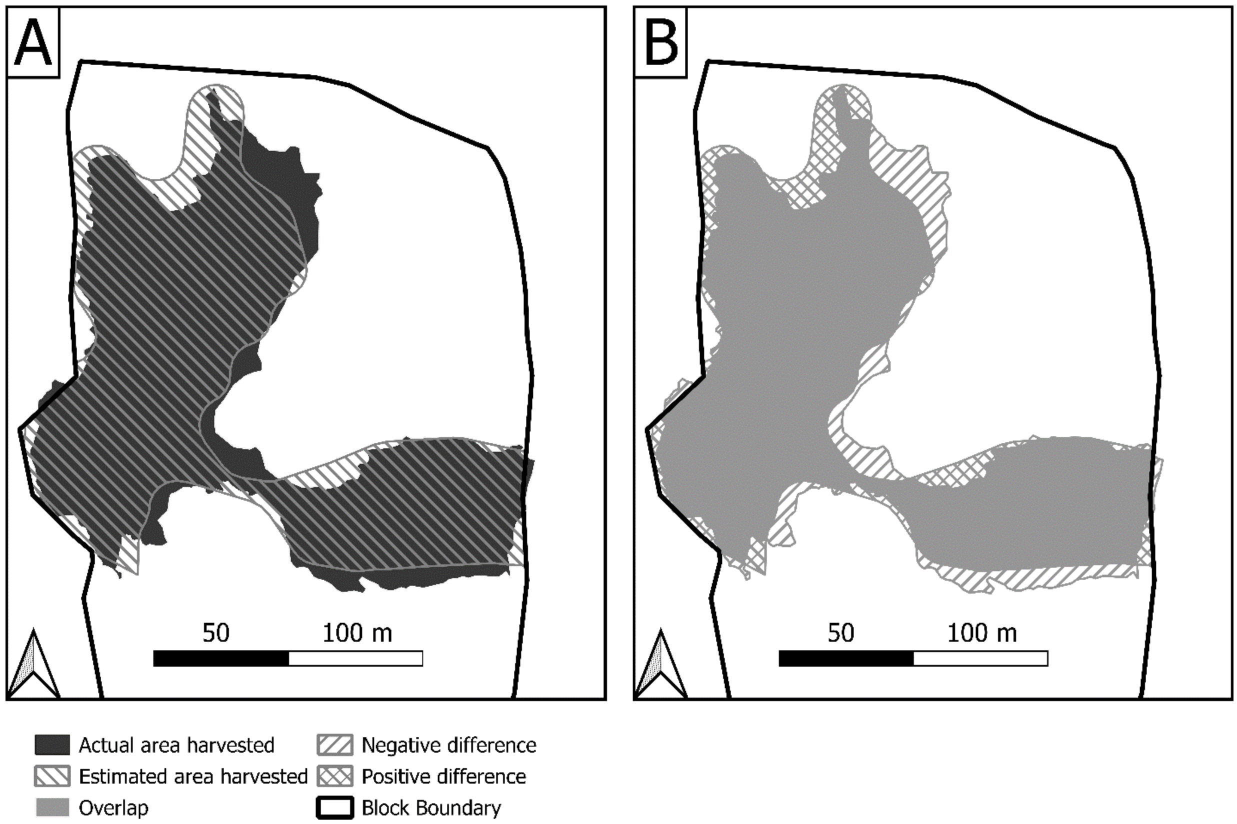


*Figure 5.3 Example of area covered analysis for FB1 day 4, A showing the observed area harvested and the estimated area harvested, B showing the positive differences, negative differences, and overlap.*

For the comparison of production metrics between remotely and in-field collected data, only days with full coverage of direct monitoring of productive time and area covered were included in the analysis of this study. The differences between observed and estimated metrics were quantified as errors in terms of productive time, area covered, volume harvested, and productivity. Error measurements included the total aggregated errors, machine-level errors, and errors at day-level expressed in absolute and relative terms, the RMSE, and the CV(RMSE), with the individual days serving as observational units.

A detailed analysis at element-level was conducted to better understand discrepancies between observed and estimated productive times. Since FPDat II data cannot discriminate between individual work elements, the elements detected from the video-based time study were classified as either productive (felling, bunching, moving, clearing, and delays < 15 minutes) or non-productive (delays > 15 minutes). The time series generated by in-field observations and remote tracking were compared at a one-second resolution. This allowed for the calculation of absolute and relative errors for each work element.

## 5.3 Results

### 5.3.1 Productive Time Analysis

The detailed time study identified that 94.8 $PMH_{15}$ (89.3%) of the 106.3 hours of observation consisted of productive work elements (Figure 5.4). Specifically, productive work elements were distributed as follows: 25.2 hours (23.7%) on bunching, 21.3 hours (20.1%) on moving, 19.1 hours (18.0%) on clearing, 18.3 hours (17.2%) on felling, and 10.9 hours (10.3%) on productive delays. Non-productive delays comprised only 10.7% of the total observed time. Similarly, the automated time analysis identified 95.6 $PMH_{15}$ (90.0%) of the observed time to be productive.

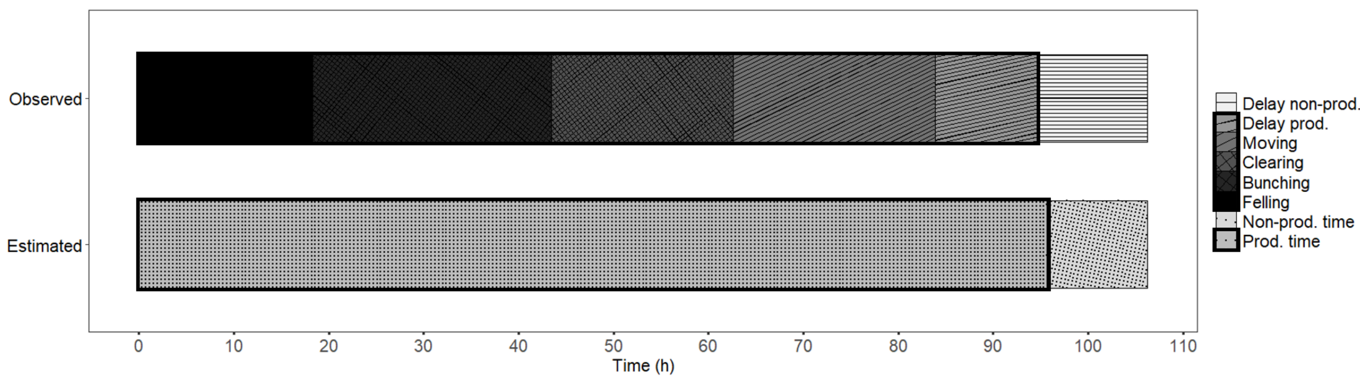


*Figure 5.4 Work-element time distribution for total time observed and total time estimated. The bold frame indicates the portions of productive time.*

At more granularity, the direct observation recorded productive times at machine-level ranging from 17.0 to 42.9 $PMH_{15}$ and from 5.9 to 12.7 $PMH_{15}$ at day-level (Table 5.2). Correspondingly, estimated time metrics from automated analysis indicated a range from 17.3 to 43.4 $PMH_{15}$ at machine-level and 6.3 to 12.7 $PMH_{15}$ at day-level.

*Table 5.2 Comparison of productive time observed (Obs.) and productive time estimated (Est.), showing the error at day- and aggregated levels. Negative errors indicate an underestimation by the automated analysis, while positive errors indicate an overestimation.*

| ID | Day | Obs. ($PMH_{15}$)[a] | Est. ($PMH_{15}$)[a] | Error (%)[a] |
|---|---|---|---|---|
| FB1 | 1 | 12.66 | 12.66 | 0.0 |
| FB1 | 2 | 11.99 | 12.00 | 0.1 |
| FB1 | 3 | 12.41 | 12.40 | -0.1 |
| FB1 | 4 | 5.87 | 6.34 | 8.2 |
| FB1 total | | 42.93 | 43.39 | 1.1 |
| FB2 | 1 | 9.21 | 9.24 | 0.3 |
| FB2 | 2 | 8.98 | 9.00 | 0.2 |
| FB2 | 3 | 9.15 | 9.17 | 0.2 |
| FB2 | 4 | 7.56 | 7.56 | 0.0 |
| FB2 total | | 34.90 | 34.97 | 0.2 |
| FB3 | 1 | 8.75 | 9.03 | 3.2 |
| FB3 | 2 | 8.24 | 8.25 | 0.1 |
| FB3 total | | 16.99 | 17.28 | 1.7 |
| Observation total | | 94.82 | 95.64 | 0.9 |

[a] Values rounded

The discrepancy between observed and estimated productive times was minimal, at 0.82 $PMH_{15}$ (0.9%). Machine-level differences ranged from 0.2% to 1.1%, while fluctuation between -0.1% and 8.2% were noted at day-level. The RMSE was recorded at 0.18 $PMH_{15}$, with a CV(RMSE) at 1.9%. The smallest recorded difference was a mere 3 seconds (FB2 on day 4).

Further the error analysis at element-level demonstrated that automated analysis of FPDat II data was highly accurate in classifying felling and bunching events as productive, showing zero discrepancies (Figure 5.5). Minor inaccuracies were observed in identifying clearing and moving tasks as productive, with error rates of 0.03% (21 seconds) and 0.13% (97 seconds), respectively. For delays, the system incorrectly classified 11.6 minutes (1.77%) of delays under 15 minutes as non-productive, thus excluding them from productive time calculations. Additionally, a higher error rate of 12.31%, equivalent to 63 minutes, was noted for delays exceeding 15 minutes, which were erroneously included in the productive time calculations.

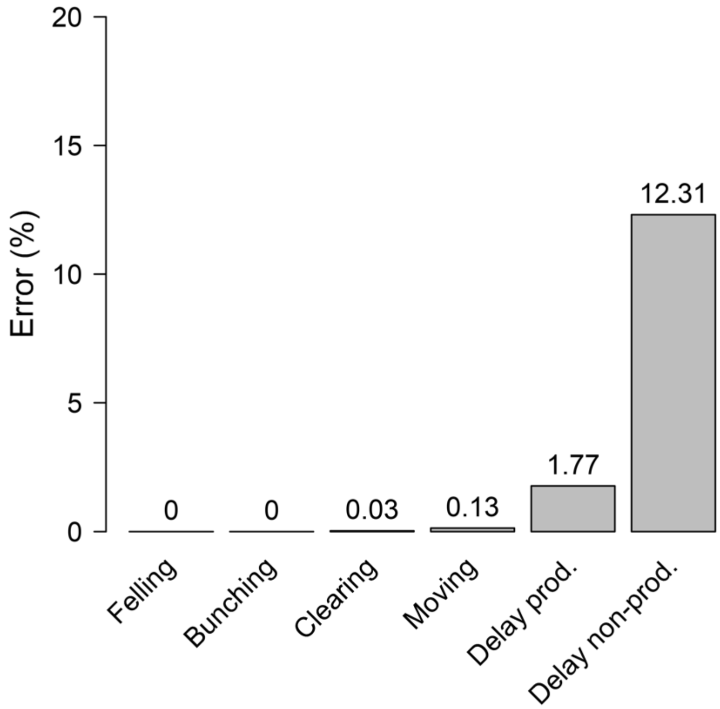


*Figure 5.5 Percent errors of work elements felling, bunching, clearing, moving, delays shorter than 15 minutes (Delay prod.), and delays longer than 15 minutes (Delay non-prod.) comparing observed time with automatically analysed time metrics.*

### 5.3.2 Area Covered and Related Volume Allocations

By applying a buffer equivalent to the machines' boom reach at the simplest application approach (1 * machine reach) to the FPDat II recorded machine tracks, an error range from 0.5% to 34.6% was noted at day-level with a mean of 9.8% (Figure 5.6). This error corresponded to an underestimation in area of 0.12 ha with a mean overlap between observed and estimated area measured at 79.2%. At the machine-level, the error ranged from 5.4% to 13.7% with mean of 10.5% representing an underestimation of 0.65 ha with a mean overlap of 74.8% for this base line scenario (Figure 5.7). After conducting the sensitivity analysis of all 25 different buffer combinations, the combination of machine reach 'boom reach + 25%' and factor '2' (2 * machine reach – 1 * machine reach) was chosen for the automated estimation of area covered based on GNSS tracks. This decision was based on the comparably small range of error (1.31% to 22.9%), low mean of the error of 9.2% and its great mean overlap of 82.6% at day-level, and the low mean error of 3.3% and high overlap of 81.4% at machine-level. However, less weight was given to the error analysis at machine-level as it was based on three observation points only. Moreover, a frequency analysis revealed that this buffer combination more frequently exhibited the lowest mean error and the highest overlap compared to other tested combinations. Decreasing the machine reach to 'boom reach' generally resulted in lower mean errors while simultaneously reducing overlap. Within the machine reach classes '+50%'; '+75%'; and '+100%' the highest mean error and lowest mean overlap was found at the buffer application '3', reaching 21.9% and 70.1% in the class '100%'. Conversely, within the machine reach classes 'boom reach' and '+25%' the error was highest and the overlap lowest at the simple buffer application 1.

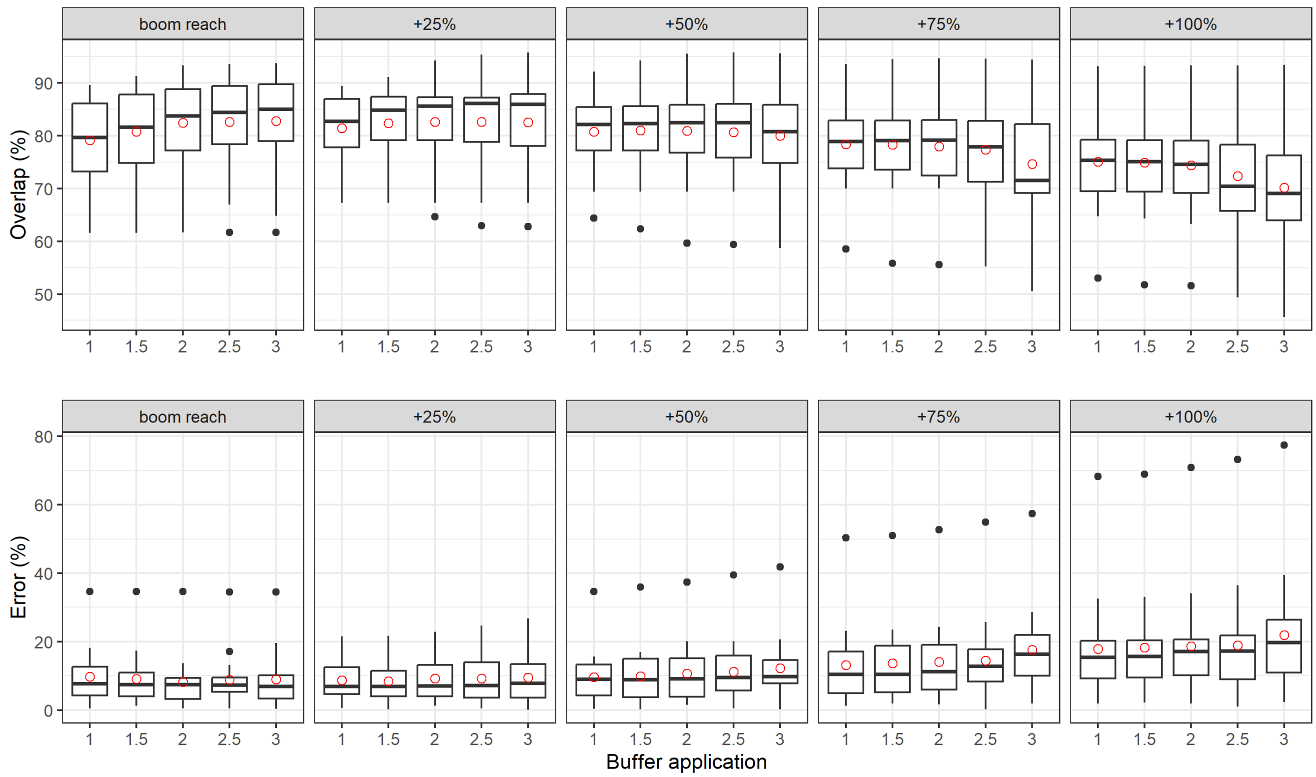


*Figure 5.6 Error and overlap analysis at day-level for all 25 different combinations of machine reach (boom reach; +25%; +50%; +75%; +100%) and buffer application (1; 1.5; 2; 2.5; 3). Circles represent mean values.*

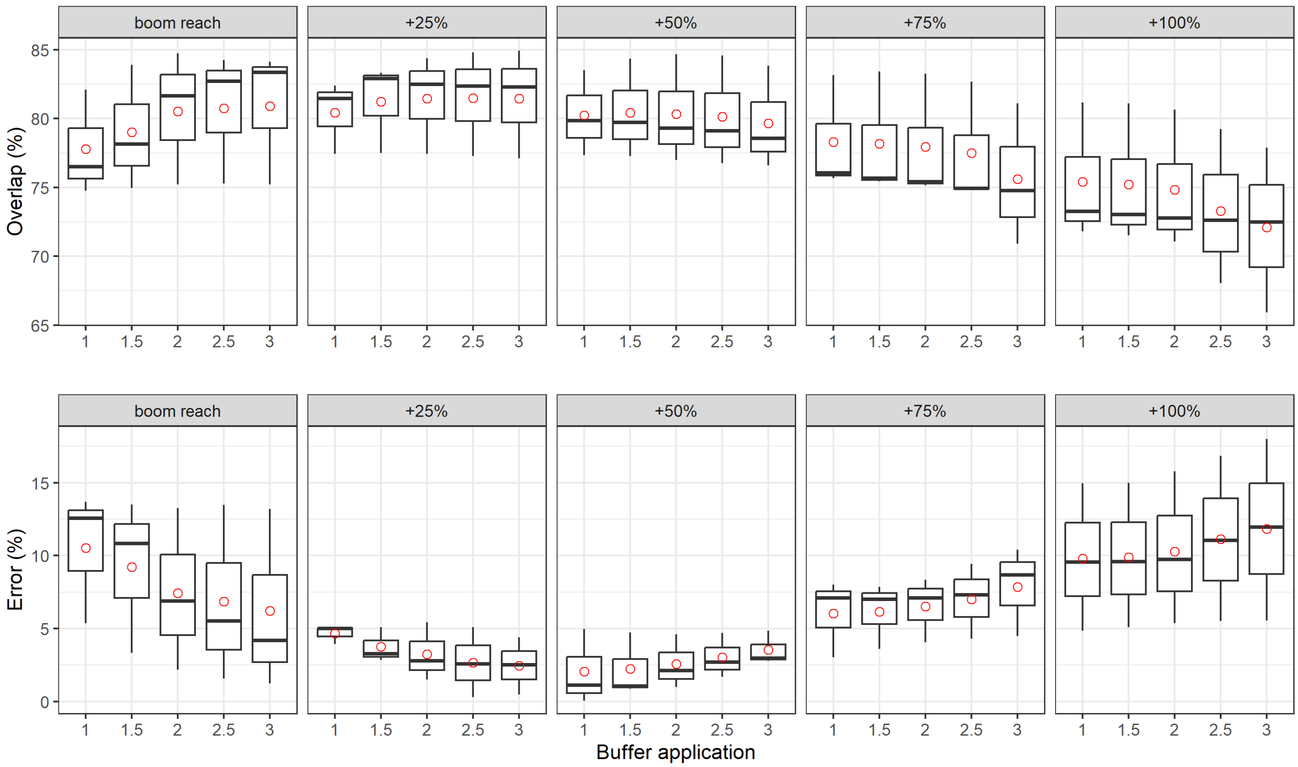


*Figure 5.7 Error and overlap analysis at machine-level for all 25 different combinations of machine reach (boom reach; +25%; +50%; +75%; +100%) and buffer application (1; 1.5; 2; 2.5; 3). Circles represent mean values.*

Orthomosaic photos delineated an aggregated observation total area covered of 14.29 ha, distributed as 6.96 ha at cutblock A, 5.63 ha at cutblock C, and 1.70 ha at cutblock D (Table 5.3). Daily areas covered ranged from 0.62 to 2.46 ha. In contrast, the automated estimation using the combination of 'boom reach +25%' and the buffer application '2' reported a slightly lower aggregated total area of 14.03 ha, with the individual cutblocks A, C, and D recording 7.08 ha, 5.34 ha, and 1.61 ha respectively, and daily ranges from 0.63 to 2.35 ha.

*Table 5.3 Comparison of observed area covered (Obs.) and estimated area covered (Est.), showing positive differences (+Diff.), negative differences (- Diff.), total differences (Tot. diff.), overlap, and the error at day- and aggregated levels. Negative errors indicate an underestimation by the automated analysis, while positive errors indicate an overestimation.*

| ID | Day | Obs. (ha)[a] | Est. (ha)[a] | + Diff. (ha)[a] | - Diff. (ha)[a] | Tot. diff. (ha)[a] | Error (%)[a] | Overlap (%)[a] |
|---|---|---|---|---|---|---|---|---|
| FB1 | 1 | 2.46 | 2.35 | 0.11 | -0.22 | -0.11 | -4.5 | 90.9 |
| FB1 | 2 | 1.98 | 2.24 | 0.75 | -0.49 | 0.26 | 12.9 | 75.5 |
| FB1 | 3 | 1.90 | 1.86 | 0.20 | -0.24 | -0.04 | -2.1 | 87.3 |
| FB1 | 4 | 0.62 | 0.63 | 0.09 | -0.08 | 0.01 | 1.3 | 87.3 |
| FB1 total | | 6.96 | 7.08 | 0.87 | -0.75 | 0.12 | 1.6 | 89.2 |
| FB2 | 1 | 1.35 | 1.16 | 0.09 | -0.28 | -0.19 | -14.0 | 79.6 |
| FB2 | 2 | 1.44 | 1.51 | 0.15 | -0.08 | 0.07 | 4.8 | 94.2 |
| FB2 | 3 | 1.45 | 1.41 | 0.16 | -0.20 | -0.04 | -2.7 | 86.4 |
| FB2 | 4 | 1.39 | 1.26 | 0.13 | -0.26 | -0.13 | -9.4 | 81.0 |
| FB2 total | | 5.63 | 5.34 | 0.23 | -0.52 | -0.29 | -5.1 | 90.8 |
| FB3 | 1 | 0.86 | 0.95 | 0.20 | -0.11 | 0.09 | 10.0 | 87.4 |
| FB3 | 2 | 0.84 | 0.66 | 0.10 | -0.28 | -0.18 | -21.6 | 67.2 |
| FB3 total | | 1.70 | 1.61 | 0.29 | -0.38 | -0.09 | -5.4 | 76.0 |
| Observation total | | 14.29 | 14.03 | 1.42 | -1.68 | -0.26 | -1.9 | 89.0 |

[a] Values rounded

The overall discrepancy in the area covered between the two methodologies amounted to a small underestimation of -0.26 ha (-1.9%), with machine-level discrepancies ranging from a -5.4% underestimation to a 1.6% overestimation, and day-level variances from -21.6% to 12.9%. The smallest difference in area coverage was 1.3% at day-level. The RMSE for area discrepancies was calculated to be 0.13 ha, with a CV(RMSE) of 9.6%. Overlaps between estimated and observed areas varied widely between individual shifts from 67.2% to 94.2%, though they were more consistent at block-level, ranging from 76.0% to 90.8%. Similarly, negative and positive differences in area varied considerably from -0.08 to -0.49 ha and from 0.09 to 0.75 ha at day-level, respectively. Notably, the estimated area for FB3 was compromised due to the proximity of several machines not equipped with FPDat II data loggers. Nonetheless, FB3 was included in this study to highlight the limitations of incomplete OBC coverage in felling operations. Excluding FB3 data, the total aggregated difference in area covered was -0.18 ha (-1.43%).

Adjusting the inventory volume to the actual scaled volume yielded conversion factors of 0.968, 0.556, and 0.899 for cutblocks A, C, and D respectively. This adjustment led to a total aggregated volume harvested of 5,298 $m^3$, according to the field observations, with volumes ranging from 934 $m^3$ at cutblock D to 2,365 $m^3$ at cutblock A (Table 5.4). At day-level volumes harvested were observed between 184 and 696 $m^3$ in the field. Analysis of FPDat II data revealed a slightly lower total aggregated volume harvested of 5,064 $m^3$, which varied from 878 to 2,230 $m^3$ at machine-level and from 178 to 669 $m^3$ at day-level.

*Table 5.4 Comparison of zonal statistics of net merchantable volume harvested derived from observed area harvested (Obs.) and estimated area harvested (Est.), showing the error at day- and aggregated levels. Negative errors indicate an underestimation.*

| ID | Day | Obs. ($m^3$)[a] | Est. ($m^3$)[a] | Error (%)[a] |
|---|---|---|---|---|
| FB1 | 1 | 696 | 646 | -7.2 |
| FB1 | 2 | 579 | 623 | 7.6 |
| FB1 | 3 | 540 | 509 | -5.7 |
| FB1 | 4 | 184 | 178 | -3.3 |
| FB1 total | | 1999 | 1956 | -2.2 |
| FB2 | 1 | 686 | 584 | -14.9 |
| FB2 | 2 | 639 | 669 | 4.7 |
| FB2 | 3 | 543 | 521 | -4.1 |
| FB2 | 4 | 497 | 456 | -8.2 |
| FB2 total | | 2365 | 2230 | -5.7 |
| FB3 | 1 | 472 | 525 | 11.2 |
| FB3 | 2 | 462 | 353 | -23.6 |
| FB3 total | | 934 | 878 | -6.0 |
| Observation total | | 5298 | 5064 | -4.4 |

[a] Values rounded

The total discrepancy in the volume harvested was calculated at -234 $m^3$, resulting in an error of -4.4%. The errors showed low variation, ranging from -6.0% to -2.2% at the machine-level, however, a larger error range from -23.6% to 11.2% at the day-level. Notably, the smallest variance observed was -3.3%, corresponding to a discrepancy of just -6 $m^3$ at the day-level. Furthermore, the RMSE was determined to be 58 $m^3$, with the CV(RMSE) recorded at 10.9%. When data from FB3 was excluded, the total error slightly improved to -4.1%.

### 5.3.3 Productivity

The integration of productive time and volume harvested revealed an overall productivity rate of 55.9 $m^3$ $PMH_{15}^{-1}$ across all directly observed days (Table 5.5). At the machine-level, productivity averaged between 46.6 and 67.8 $m^3$ $PMH_{15}^{-1}$, while day-level productivity varied more widely, ranging from 31.3 to 74.5 $m^3$ $PMH_{15}^{-1}$. In comparison, the estimated overall productivity was slightly lower, decreasing by 3 $m^3$ $PMH_{15}^{-1}$, spanning from 45.1 to 63.8 $m^3$ $PMH_{15}^{-1}$ at machine-level, and from 28.1 to 74.3 $m^3$ $PMH_{15}^{-1}$ at the day-level.

*Table 5.5 Comparison of observed productivity (Obs.) and estimated productivity (Est.), showing the error at day- and aggregated levels. Negative errors indicate an underestimation by the automated analysis, while positive errors indicate an overestimation.*

| ID | Day | Obs. ($m^3/PMH_{15}$)[a] | Est. ($m^3/PMH_{15}$)[a] | Error (%)[a] |
|---|---|---|---|---|
| FB1 | 1 | 55.0 | 51.3 | -6.7 |
| FB1 | 2 | 48.3 | 51.9 | 7.5 |
| FB1 | 3 | 43.5 | 41.0 | -5.7 |
| FB1 | 4 | 31.3 | 28.1 | -10.2 |
| FB1 total | | 46.6 | 45.1 | -3.2 |
| FB2 | 1 | 74.5 | 63.2 | -15.2 |
| FB2 | 2 | 71.2 | 74.3 | 4.4 |
| FB2 | 3 | 59.3 | 56.8 | -4.2 |
| FB2 | 4 | 65.7 | 60.3 | -8.2 |
| FB2 total | | 67.8 | 63.8 | -5.9 |
| FB3 | 1 | 53.9 | 58.1 | 7.8 |
| FB3 | 2 | 56.1 | 42.8 | -23.7 |
| FB3 total | | 55.0 | 50.8 | -7.6 |
| Observation total | | 55.9 | 52.9 | -5.4 |

[a] Values rounded

The discrepancy in the total productivity resulted in an error of -5.4%, which improved to -4.8% when excluding the FB3 data. Productivity variations at machine-level were relatively minor, ranging from -7.6% to -3.2%, indicating small underestimations. However, at day-level, these differences were observed with higher variation between -23.7% and 7.8%. The RMSE for productivity reached 6.4 $m^3$ $PMH_{15}^{-1}$, with a CV(RMSE) of 11.5%. The smallest difference at day-level was observed for FB2, with a slight underestimation of -4.2% or -2.5 $m^3$ $PMH_{15}^{-1}$.

## 5.4 Discussion

This chapter presents a pioneering approach to fully automated production analysis based on remotely collected FPDat II data by demonstrating its potential for feller buncher harvesting operation monitoring. The minor discrepancies between field data and the automated analysis of FPDat II data at a higher level of aggregation confirm the approach's effectiveness for block-level production analysis and fall within the tolerable error range of the FMC project's collaborating industry partners. A high confidence of field data accuracy, due to video recordings offering a clear digital timeline that could be reviewed multiple times for time study analysis, underscores the strength of this study. Increasing error rates were noticed with finer granularity of observation level, partially explained by the approach's limitation of recording low-frequency GNSS position points to keep satellite data transfer costs low. Since the automated analysis of production metrics using FPDat II data was only validated in its initial phase, full coverage of OBCs (i.e., equipping every machine working in the same cutblock with an FPDat II data logger) could not be ensured for every study site. In the case of cutblock D, several felling machines working in proximity to areas covered by FB3 (during and previous to the observation) were not tracked by the system, impacting the estimated production metrics. Therefore, results from cutblock D should be viewed as examples for incomplete monitoring. Even though the study was not able to collect data for entire cutblocks, an aggregation of observation to machine-level already showed a reduction in error. This was particularly evident in the metrics of area covered, volume harvested, and ultimately, productivity. Once full FPDat II coverage of machines is provided, errors are expected to be minimal in future studies that look at larger aggregations. Moreover, it is important to note that the limited number of observations (10) poses a constraint on this study. To effectively evaluate the automated analysis approach, complete data coverage of each shift was essential, as the area covered was determined through pre- and post-shift orthomosaic image analysis. Consequently, any days with compromised data collection were excluded from the analysis.

The aggregated errors were notably low, with -0.9% (0.82 $PMH_{15}$) for productive time and -1.9% (-0.26 ha) for area covered. Errors were slightly higher for volume harvested and productivity, at 4.4% (-234 $m^3$) and -5.4% (-3 $m^3$ $PMH_{15}^{-1}$) respectively. These findings corroborate the results of Chapter 4, who provided fundamental recommendations for the analysis of productive time in FPDat II data. Even at day-level, the error rate for estimated productive time remained low, with a CV(RMSE) of 1.9% and a maximum difference of 0.47 hours observed in one individual shift. Slightly greater discrepancies were observed for all other metrics at day-level, as indicated by the CV(RMSE)s of 9.6%, 10.9%, and 11.4% for area covered, volume harvested, and productivity, respectively. The highest errors for every metric at day-level were observed for FB3. Excluding FB3 data to limit errors from a compromised recording system allowed reductions in error rates by 0.5, 0.3, and 0.5 percentage points for area covered, volume harvested, and productivity, respectively. Although the exclusion of FB3 data had a minimal impact on the overall errors, it more significantly affected the CV(RMSE), resulting in values of 8.5% for area covered, 8.9% for volume harvested, and 9.3% for productivity.

The most significant errors in remotely collected time data occurred when non-productive machine movements during delays exceeded duration thresholds for time classification introduced in Chapter 4 and were, therefore, incorrectly recorded as productive periods. For instance, on day 4 of the FB1 observation, 0.47 hours were mistakenly classified as productive, leading to an error of 8.2% due to machine movements of 94 seconds during a mechanical delay for maintenance.

Element-level analysis revealed that delays shorter and longer than 15 minutes were the primary sources of discrepancies, with error rates of 1.8% (0.19 hours) and 14.3% (1.05 hours), respectively. Other work elements such as felling, bunching, moving, and clearing were detected as productive with high accuracy. Generally, discrepancies in accurately recording delays were not due to malfunctioning FPDat II units. However, these differences underscore that a fully automated data collection system is based on assumptions and cannot accommodate events that deviate from these expectations. The productive time analysis logic developed in Chapter 4 was chosen for its proven precision, in contrast to the default settings of FPDat II time metric estimation, as explored by Pellegrini et al. (2013).

Although the sensitivity analysis of the 25 different combinations of buffer sizing and application approaches did not reveal an optimal solution, a machine reach of ‘boom reach + 25%’ and the buffer application ‘2’ were chosen for the automated area analysis due to the combination’s overall low mean errors, small error ranges, and significant overlaps at both machine- and day-level. Even though lower mean errors were observed in the machine reach classes ‘boom reach’ and ‘boom reach + 50%’ at day-level and machine-level respectively, the ‘boom reach + 25%’ class proved to be the optimal choice, exhibiting the lowest mean errors across both levels. Within the ‘boom reach + 25%’ class, buffer application ‘2’ demonstrated the greatest mean overlap at both analysis levels. It also represented a balance point, with decreasing mean errors at the machine-level and increasing mean errors at the day-level as multipliers in the application increased.

Using the combination of ‘boom reach + 25%’ and buffer application ‘2’, disparities between the observed and estimated area covered were noted to vary largely at day-level. Despite the relatively low RMSE of 0.14 ha, discrepancies for individual days were recorded, with a maximum error of 0.25 ha. These discrepancies can partially be attributed to the logic applied to delineate polygons from machine paths representing the area covered. On the first day of the FB2 study, a notable discrepancy of -14% was observed with a negative difference of -0.28 ha and a positive difference of only 0.09 leading to an overlap of 79.6%. This difference largely stems from the feller buncher navigating around a patch of trees without felling them prior to the observation. The gap-closing buffering approach, combined with infrequent GNSS point recording by the FPDat II units, mistakenly classified this area as felled. Due to the systematically applied machine reach, every feller buncher is assumed to always be cutting to its maximum reach. Consequently, the estimated widths for entry and exit paths into and out of the cutblocks, for example, may be wider than they are. For instance, the entry path for FB2 was cut before monitoring began, leading to an overestimation of the area cut prior to the study. This discrepancy additionally contributed to the underestimation of area covered of -0.19 ha on the first day of observation. Nevertheless, automated analysis was found to underestimate the areas covered at machine-level overall.

Another important factor specifically affecting the estimation of area covered in this study is the operational context. On the first observation day, FB3 operated closely alongside two other felling machines, one of which wasn't equipped with an FPDat II unit. Consequently, the automated analysis approach failed to account for the area cleared by the unequipped machine, inaccurately attributing parts of it to FB3 instead. Additionally, on the second day, a GNSS error affected the FPDat II data from a machine working adjacent to the area FB3 felled. The compromised polygon created for that machine had a significant impact on the estimated area covered for FB3. Across both observation days for FB3, the differences in area covered were considerable, with discrepancies of 10% and -21.6%, and an overlap of only 67.2% on the second day. Although it's challenging to mitigate errors from GNSS signals under tree canopies (Bettinger and Merry, 2012; Brach and Zasada, 2014; McGaughey et al., 2017), these relatively large discrepancies highlight the need to equip and monitor all machines with properly functioning and calibrated FPDat II units, ensuring comprehensive coverage during remote automated production analysis. Operational circumstances also partially explained the discrepancies in area coverage for FB1. When multiple feller bunchers work closely together, the automated system credits the first machine to traverse an area with the associated volume if the machines pass through on different days, even if it did not actively fell trees but simply cut a narrow path. While these assumptions are typically reasonable, reality can sometimes deviate, causing discrepancies in estimated production metrics, as observed on day 2 of the FB1 study where the area covered was overestimated by 12.9%. Incorrect attribution of volume between the two machines working closely together resulted into a negative difference of -0.49 ha and a positive difference of 0.75 ha and overlap of 75.5%. A system capable of tracking machine progress in real time could more accurately attribute area covered to individual machines. However, at this stage, the daily shift analysis does not allow for further refinement.

The volume felled per area covered was determined using LiDAR inventory data to create a volume distribution map that dispersed the scaled volume throughout the cutblock. Consequently, another assumption in the automated production analysis is the uniformity of volume distributions from both the inventory and the felled (scaled) volume. This approach proved particularly crucial at cutblock C, where the application of a 0.556 conversion factor underscored the importance of high-quality inventory data. Although the scaled volume does not directly reflect machine productivity - due to the exclusion of breakage or unprocessed defective stems - it was considered more accurate than potentially outdated inventory data for this study. However, since the scaled volume for the entire cutblock is typically unavailable until harvesting operations are completed, the inventory volume information can temporarily serve for daily productivity estimations and be updated through a reconciliation process post-harvesting. Zonal statistics of the volume distribution further indicated that discrepancies in harvested volume were not solely related to discrepancies in area covered. For instance, on observation day 4 of FB1, the area covered was slightly overestimated by 0.01 ha leading to a small error rate of 1.3%. However, for the same day and machine, the harvested volume was underestimated by -3.2%. Despite the comparably high overlap of 87.4% and only minor negative and positive differences of -0.08 and 0.09 ha, the differences in volume distribution between these two areas had a more pronounced effect on the volume harvested than the actual size of the area. Similarly, discrepancies in site or stand attributes such as ground slope can arise from inaccuracies in detecting area covered, potentially impacting productivity modelling based on automated data collection.

Like the comparison of productive time, the accuracy of estimated area coverage and volume harvested also improves with increased levels of aggregation. For each machine, the most significant discrepancies at day-level were remarkably larger than those observed at the aggregated level. The days with the greatest productivity discrepancies consistently matched those with the largest differences in area covered within each study. Given the minimal discrepancies in productive time, it is reasonable to conclude that variations in productivity were primarily due to disparities in area covered. However, as previously mentioned, the extent of overlap between actual and estimated harvested areas, indicated by larger positive and negative differences, and the resulting differences in zonal statistics also significantly influence daily productivity rates.

Previous research has shown that incorporating operator activity input can add detail to FPDat technology data, albeit at the cost of transforming it into a semi-automated data collection system (Evanson 2009). However, Pellegrini et al. (2013) noted that stop codes and operator login data proved to be unreliable, particularly in long-term monitoring. Improving the precision of detected area coverage is crucial for enhancing the accuracy of fully automated day-level production metrics. A potential solution could be to increase the GNSS location point recording frequency of the FPDat II units. However, such an enhancement would also lead to higher costs due to increased satellite communication between the FPDat II units and the cloud server, resulting from the larger volume of data transmission. The trade-off between cost increases and accuracy gains may vary among users.

Despite the variability in day-level error rates observed in this study, the presented approach to fully automated production analysis not only enables long-term operation monitoring and large-scale management but also provides a foundation for establishing logging rate estimates. Automated production information analysis could fundamentally change forest operation practices, significantly enhancing productivity. Although not as detailed as in-field observations that measure productivity at the cycle level, this work represents the first automated approach to collect and analyse key production metrics in WT feller buncher harvesting operations. The estimated aggregated metrics from FPDat II data analysis offer more detailed insights into operations than common block-level analysis, enabling better productivity estimation by accurately recognizing deviations from operational plans. This precision allows for a more accurate estimation of productivity for individual machines without needing to aggregate all machine data based on the entire harvested volume. Performance is expected to improve with full monitoring coverage, as each machine equipped with an FPDat II unit contributes to more informed decision-making and performance improvement strategies on a daily basis. Nevertheless, the findings caution that even uncompromised estimated day-level metrics may not fully align with actual figures due to limitations from reduced GNSS recording frequency, underscoring the need for a critical examination of daily production analysis results. This level of detail enhances analysis resolution by isolating individual machines and identifying specific productivity-influencing factors, ultimately leading to a more granular and insightful understanding of machine efficiency and performance, and opening up possibilities to improve resource allocation and enhance competitiveness.

## 5.5 Conclusion

This study critically assessed an approach for fully automated remote feller buncher production analysis using FPDat II data, comparing it with field-observed data. The findings affirm the approach's robustness, particularly highlighting its minor discrepancies in productive time at every level of observation. At the aggregated level, recorded errors were overall small, indicating strength in the use of estimated production metrics for block-level analysis. The estimated day-level metrics - area covered, volume harvested, and productivity - showed more considerable discrepancies. However, these errors predominantly stem from inaccurately delineating the area covered by the machines. This issue is partially attributed to the approach's operational logic but also to incomplete instrumentation of FPDat II units in individual cases, and errors were reduced after the exclusion of compromised data. While errors were generally minor, the logic's susceptibility to inaccuracies in area covered at the day-level underscores the potential for further refinement.

Looking ahead, future research will aim to further validate the capabilities of fully automated production analysis based on FPDat II data across various machinery types, thereby broadening its applicability. Efforts will focus on enhancing the approach's accuracy at the day-level and on investigating methods to improve delineation accuracy, potentially through the incorporation of operator activity input. Simultaneously, it will be important to automatically exclude potentially corrupted data, such as when two consecutive GNSS points exceed predefined distances, indicating GNSS inaccuracies.

Moreover, with a growing database of production information from fully automated analysis, creating productivity models for various types of machinery becomes feasible. Future research aims to incorporate a comprehensive dataset, detailing the productivity of different machines at the block-level, with the intent to develop a benchmarking module and creating an environment for sophisticated productivity modelling. This extensive approach seeks to establish it as a comprehensive analytical tool for data-driven forest operations management.

In sum, fully automated production information analysis based on FPDat II data stands as a promising tool for production monitoring in forestry. Acknowledging its current limitations at day-level, this study paves the way for the analysis approach to evolve into a more refined system that can offer detailed, reliable insights for the enhancement of forest operations.

# Chapter 6 - Modeling Feller Buncher Productivity in Whole-Tree Harvesting: A Long-Term Data-Driven Approach

## 6.1 Background and Objectives

Building on insights from previous studies on WT harvesting productivity modeling, this chapter aims to develop explanatory productivity models for feller bunchers using an extensive dataset. Additionally, it presents a systematic methodology for analyzing large-scale, long-term production data. The models use long-term production information of feller bunchers retrieved from FPDat II data loggers, which provide standardized data collection across diverse harvesting operations and enable the productivity analysis on a large scale. The three key factors - stem size, ground slope, and stand density in terms of volume per hectare and stems per hectare - were incorporated into the model, aligning with previous findings in Chapter 3, which highlighted piece size and ground slope as the most commonly studied site and stand-related factors in WT harvesting productivity research.

The analysis presented in this chapter is two-staged, focusing on explaining the influence of various variables on productivity. First, a daily machine-level analysis accounts for variability within and between cutblocks and days. Second, daily reports are aggregated to the cutblock level, offering a broader perspective on how the same explanatory variables affect productivity on a per-block basis.

Additionally, the chapter defines outlier exclusion criteria to ensure accurate productivity estimates by following the recommendations of Chapter 5 for excluding compromised area covered estimates. It also proposes a systematic approach for identifying abnormal production data that may require further investigation. By detailing a step-by-step modeling approach, it offers a practical, tutorial-like framework for industry practitioners and researchers aiming to replicate large-scale productivity analyses.

Ultimately, this research fills a critical gap in the forest industry's digital transformation by providing actionable insights into WT felling productivity, thereby supporting future advancements in machine performance management and decision-making.

## 6.2 Material and Methods

### 6.2.1 Study Sites and Machines

The data included in this study consists of daily production information reports of feller bunchers contracted by the two FMC-collaborating forest products companies. All machines were feller bunchers of various engine sizes, weight classes, and years of manufacturing. A machine classification system existed for both companies, however, the system was not consistently updated, consequently the machine ages were not available. The following makes and models were included in this study: John Deere 903K-II, 903M, 959M; Link-Belt 290LX; Madill 2250; Tigercat LX830, LX830D, LX830E, L855, 870C, 870D, L870, L870C, LX870, LX870D, X870C, X870D. Attached to these base machines were 24” – 26” circular saws.

A total of 9,865 daily production reports were collected from ground-based WT harvesting operations conducted between January 2022 and July 2024 across British Columbia, including both the coastal forests and the interior. Species distributions within the cutblocks were representative of local BEC zones, with average stand densities ranging from 179 to 3,275 stems per hectare on average slopes of up to 47%. However, the range of average stem densities and ground slopes in cutblock subsections, as recorded in the daily production reports, was much broader, varying from 139 to 5,974 stems per hectare and reaching slopes of up to 81%.

### 6.2.2 Data collection and Analysis

To provide a guide through the applied data collection and analysis, Figure 6.1 presents a schematic overview of the workflow, beginning with data recording and ending with model comparison and interpretation.

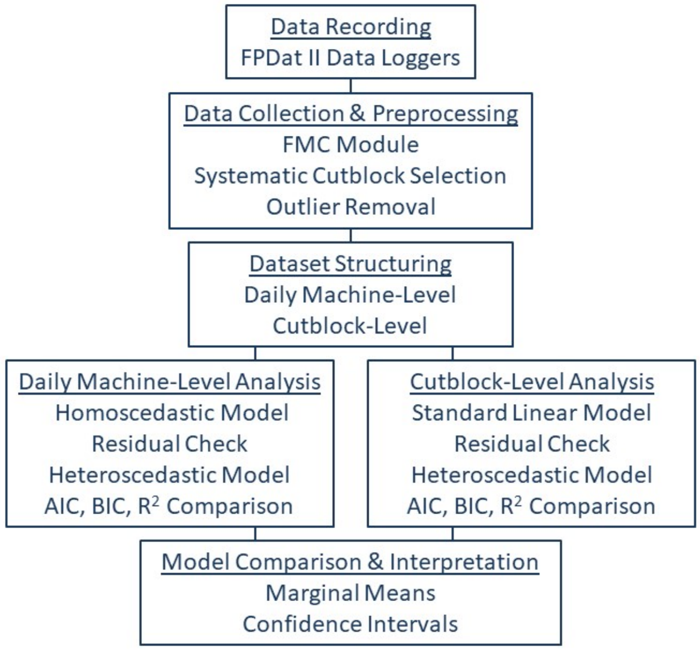


*Figure 6.1 Schematic overview of the workflow applied in this chapter.*

Production reports for this study were retrieved from the FMC Module of Op Tracker (hereafter referred to as the FMC Module). This digital tool was developed as part of the FMC project by Lim Geomatics in collaboration with the UBC and the two forest products companies involved in the project. The FMC Module is a cloud-based system that processes FPDat II data, integrates it with volume distribution maps and inventory data, and provides fully automated production monitoring analysis for timber harvesting systems. This tool enables users to monitor operational status and performance by selecting individual machines or entire harvesting units. The application provides daily production metrics for individual machines and aggregates this information over selected time periods or at the cutblock-level.

In addition to tracking daily machine productivity, the FMC Module calculates metrics such as area coverage (expressed as a percentage of total cutblock area) and overall production progress for harvesting units.

The production reports include a wide range of metrics and information, such as:

- Production Metrics:
  - Start and stop time
  - Utilization (%)
  - Engine on time (s)
  - Idle time (s)
  - Productive time ($PMH_{15}$)
  - Delay-free productive time ($PMH_0$)
  - Area covered (ha)
  - Merchantable volume harvested ($m^3$)
  - Productivity ($m^3/PMH_{15}$)
- Terrain and Environmental Variables:
  - Average volume per tree ($m^3$/tree)
  - Average volume per hectare ($m^3$/ha)
  - Average stem density (trees/ha)
  - Average ground slope (%)
  - Ground slope classes (% of area in 10% slope intervals)
  - Hours of daylight (h/day)
  - Soil type (currently undefined)
  - Ground roughness (currently undefined)
  - Understory (currently undefined)
- Operational Information:
  - Machine ID
  - Cutblock ID and size
  - Contractor ID
  - Operation type (e.g., felling, primary transportation, loading)
  - Machine specifications (make and model; engine size: small, medium, large; boom reach; attachment)
  - Number of sorts (n)
  - Winch-assist use (yes/no)
  - Collaboration with other machines (% area overlap)

However, at the time of data collection for this study, only four terrain and environmental variables - average volume per tree (also referred to as piece size), average volume per hectare, average stem density, and average ground slope - were consistently available for all production reports alongside the production metrics. Additionally, the operational information - machine id, cutblock ID, contractor ID, and cutblock size - were available. Other variables were either only partially available or not yet defined in their units or method of collection.

Instead of using the web-based application for data collection, the production reports were downloaded as raw data compiled into a single shapefile. In this file, each polygon represents the area covered by a production report, with corresponding metrics and details stored as attributes. After retrieving the data from the cloud server on which these reports are archived, a systematic selection of suitable cutblocks was conducted for data analysis. The aim was to exclude reports from incomplete cutblocks. To identify these cutblocks, the percentage of area covered per cutblock was calculated by aggregating the area covered by felling machines per cutblock and dividing it by the total area of the cutblock. To account for areas that were uncovered by machines but potentially hand-felled, the intersection of these uncovered areas and areas designated for hand-felling was deducted from the total cutblock area. The designated areas were identified using an existing GIS layer from the operation planning data. In a subsequent step, cutblocks that did not meet the following completion criteria were excluded from the analysis:

- Cutblocks with a coverage greater than 70% and a size of up to 10 ha;
- Cutblocks with a coverage greater than 80% and a size between 10 ha and 50 ha;
- Cutblocks with a coverage greater than 90% and a size larger than 50 ha

As a result, a list of suitable cutblocks was created for further analysis. This step was taken to prevent the inclusion of compromised production reports caused by misallocated areas due to missing recordings (e.g., machines not equipped with FPDat II units), as discussed in Chapter 5.

Another potential source of error in automated area coverage estimation is GNSS errors. Although anecdotal evidence suggests that errors in distance or time between consecutive GNSS positions occur infrequently with FPDat II data loggers, any missed coverage due to recording errors can result in an over-allocation of area covered for subsequent machines operating in the same area (as shown in Chapter 5). GNSS errors were calculated based on the data loggers' pre-set recording frequencies, which are set to record every 60 minutes or every 25 meters.

Consequently, if either the time interval between two consecutive GNSS recordings exceeded 60 minutes or the distance between them exceeded 25 meters, an error was detected. In such cases, the period of error was defined as the time between the last valid recording and the subsequent valid recording. Accordingly, cutblocks with more than three total hours of missed or erroneous GNSS recordings were excluded from the data analysis. The cutblock completion and GNSS selection criteria thresholds were established based on 15 fully completed cutblocks with either no GNSS recording errors or only minor inaccuracies. The criteria parameters were calibrated to ensure that these cutblocks were automatically included. To validate the effectiveness of the criteria, they were applied to the dataset, and 10 randomly selected cutblocks were manually analyzed.

In the next step, daily production reports recorded in the selected suitable cutblocks were extracted from the shapefile and aggregated into a dataset where each row represented one report. Production reports with an area smaller than 0.02 ha or a productive time shorter than one hour were removed, as they were considered insufficient to represent a realistic work shift. Additionally, a systematic outlier exclusion was performed by removing productivity and predictor variables values in the top and bottom 2.5% of the dataset. For the cutblock-level analysis, a second dataset was created where the harvested merchantable volume was aggregated and divided by the total productive time across daily reports for each cutblock to calculate productivity. The variables - stem size, volume per hectare, stem density, and slope percent - were averaged at the cutblock-level using an area-weighted method, based on the size of the individual areas covered in each daily report.

The objective of the data modeling was to quantify the effects of the four explanatory variables on machine productivity across all machines and blocks. The modeling was conducted at two levels: first, a primary modeling was performed using daily-level observations as repeated measures to address the statistical problem. Second, a subsequent modeling was done using aggregated data at the cutblock-level to provide an additional perspective on the relationships between the explanatory variables and productivity.

### ***Primary Modeling: Using Daily-Level Repeated Measures per Machine***

The dataset of daily production reports was used for daily machine-level analysis, in which individual daily reports served as observation points. Descriptive statistical analysis was performed, and bivariate plots (Appendix C.2.1; C.3.1) of productivity and the available explanatory variables were generated. To visualize differences in linear regression slopes between productivity and explanatory variables for individual machines, diagnostic spaghetti plots were generated (Appendix C.2.1). For further analysis of the relationship between productivity and explanatory variables at the daily machine-level, a stepwise approach was employed using mixed-effects models implemented in the nlme package in RStudio.

In the first step, a homoscedastic mixed-effects model with nested random effects was fitted. The variables average stem size, average volume per hectare, average stem density, and average slope percent were included as fixed effects, while cutblock (BlockId) and machine identifiers (MachineId) were modeled as nested random effects to account for variability not explained by the fixed effects. Model results were analyzed using the summary function in R. Residuals were plotted, both overall and for individual variables, and the marginal $R^2$ ($R^2m$) and conditional $R^2$ ($R^2c$) values (following Nakagawa and Schielzeth, 2013) were calculated to assess model fit. $R^2m$ represents the variance explained by the fixed effects alone, while $R^2c$ accounts for both fixed and random effects, providing insight into the total variance explained by the model.

Following the evaluation of the initial homoscedastic model, evidence of heteroscedasticity in the residuals encouraged the fitting of a heteroscedastic mixed-effects model. This model included the same fixed and random effects structure as the homoscedastic model but incorporated the weights argument in the nlme package, specifying a variance function varIdent(MachineId) to allow for machine-specific variability in residual variance. While the random effect estimates the variability between machines, the residual variance structure accounts for differences in within-machine residuals, hence relaxing the assumption of constant variance. The results of the heteroscedastic model were analyzed in a similar manner using the summary function, plotting residuals, and calculating the $R^2m$ and $R^2c$ values to assess the fit of the heteroscedastic variance structure. The models were then compared using the Akaike Information Criterion (AIC) (Akaike, 1974) and the Bayesian Information Criterion (BIC)

(Schwarz, 1978) to evaluate whether accounting for heteroscedasticity improved model performance.

In the final step, a sensitivity analysis was conducted to assess whether the heteroscedastic model's results were robust to machines with fewer than 10 observations. Because small sample sizes can inflate the SEs of machine-specific variance estimates under the varIdent(MachineId) structure, potentially leading to overfitting, those machines were excluded from the dataset to determine whether the model results were sensitive to their inclusion. The modified heteroscedastic model was refitted, and its results were compared to the full heteroscedastic model to determine the impact of removing machines with sparse data. This step provided insight into whether excluding low-observations machines enhanced the robustness and interpretability of the model (Appendix C.2.4).

### ***Secondary Modeling: Using Aggregated Cutblock-Level Data***

In addition to the daily machine-level analysis, a simplified approach was adopted at the cutblock-level, where each cutblock served as a single observation point. After aggregation at the cutblock-level, observations were all independent. Consequently, a standard linear model, using lm in R, was applied. The same explanatory variables used in the daily machine-level analysis were included as fixed effects. Model fit was evaluated using the summary function, and residual plots were examined to confirm that model assumptions (linearity, homoscedasticity, normality of residuals) were reasonably met.

Due to heteroscedasticity concerns, a linear fixed-effects model, using lme in the nlme package, was additionally fit for the cutblock-level analysis. Because there was only one observation per cutblock, heteroscedastic modeling by cutblock or machine was not pursued; rather, contractor id was chosen as a random effect in the case of this model. As done for the daily machine-level heteroscedastic model, results were analyzed using the summary function, plotting residuals, and calculating the marginal $R^2$ and conditional $R^2$.

As a measure of practical significance, 95% CIs were constructed for the fixed effects of every model. While p-values were reported by nlme models and are included in the Appendix C, they are not presented in the results section due to their reliance on distributional assumptions, which can limit interpretability in mixed-effects frameworks. Given the exploratory nature of this study, the focus is placed on practical rather than statistical significance, promoting a more comprehensive approach to interpreting data insights.

In all models, the intercept for the fixed effects was set to zero, as productivity cannot exist when the volume-related fixed effects are also zero. To analyze the effect of individual fixed variables on productivity, estimated marginal means were computed using the emmeans package in R, based on the heteroscedastic linear mixed-effects models. Each fixed variable (average stem size, volume per hectare, average stem density, average ground slope, and cutblocklock size for cutblock-level analysis) was systematically varied in predefined increments (0.1, 50, 200, 2.5, and 10, respectively), while all other fixed variables were held constant at their minimum observed value. This approach allowed for an isolated assessment of each predictor's effect on productivity while accounting for random effects. In all models the Broyden-Fletcher-Goldfarb-Shanno (BFGS) optimizer was used (Broyden, 1970; Fletcher, 1970; Goldfarb, 1970; Shanno, 1970).

## 6.3 Results

After applying the systematic selection criteria for suitable production reports and excluding outliers, a total of 3,081 reports were retrieved, which were relatively evenly distributed between the two companies (1,516 and 1,565 reports, respectively). These reports were generated by 71 machines (42 from one company and 29 from the other) operating across 205 cutblocks (109 and 96 per company, respectively). As the number of machines equipped with FPDat II data loggers steadily increased over the course of the project's data collection phase, more recent data is proportionally represented at a higher rate in the dataset.

Descriptive statistics, including the range, mean, median, SD, and interquartile range (IQR) for the daily machine-level observation points, are presented in Table 6.1.

*Table 6.1 Descriptive statistics for daily machine-level observation points - range, mean, median, SD, and IQR.*

| Statistic | Productivity ($m^3$/$PMH_{15}$) | Avg. piece size ($m^3$) | Avg. Volume per ha ($m^3$) | Avg. stem density (n) | Avg. ground slope (%) |
|---|---|---|---|---|---|
| Mean (SD) | 54.0 (26.1) | 0.38 (0.22) | 353.2 (169.7) | 1093 (623) | 17.9 (10.1) |
| Median (Range) | 49.6 (14.2 – 148.0) | 0.31 (0.09 - 1.32) | 333.9 (75 – 856.2) | 905 (205 - 3044) | 15.6 (1.5 - 48.9) |
| IQR | 34.9 | 0.21 | 260.9 | 904 | 13.9 |

The production reports covered a wide range of productivity (14.2 to 148.0 $m^3$/$PMH_{15}$), of operations in varying conditions. Average stem size spans from 0.09 to 1.32 $m^3$/tree, indicating harvesting of small to fairly large trees. The average volume per hectare ranges from 75 to 856.2 $m^3$ and average stem density similarly exhibits wide variation (205 to 3,044 trees/ha). Finally, average ground slope ranges from 1.5% to 48.9%, highlighting the diverse terrain in which operations were recorded.

To complement the machine-level descriptive statistics, Table 6.2 presents the same statistics at the aggregated cutblock-level.

*Table 6.2 Descriptive statistics for cutblock-level observation points - range, mean, median, SD, and IQR.*

| Statistic | Productivity ($m^3$/$PMH_{15}$) | Avg. piece size ($m^3$) | Avg. Volume per ha ($m^3$) | Avg. stem density (n) | Avg. ground slope (%) | Cutblock size (ha) |
|---|---|---|---|---|---|---|
| Mean (SD) | 70.9 (23.4) | 0.47 (0.25) | 357.4 (155.5) | 894 (538) | 17.3 (10.5) | 18.0 (16.6) |
| Median (Range) | 69.4 (20.2 – 133.1) | 0.40 (0.12 – 1.19) | 337.1 (83.2 – 752.3) | 706 (205 – 2834) | 15.3 (2.3 – 40.7) | 13.0 (0.8 – 92.3) |
| IQR | 36.4 | 0.31 | 209.3 | 658 | 17.4 | 18.3 |

Mean productivity was higher at the cutblock-level (70.9 $m^3$) than at daily machine-level (54.0 $m^3$). Similarly, mean average piece size (0.47 $m^3$) and mean average volume per hectare (357.4 $m^3$) were slightly elevated relative to daily machine-level values (0.38 $m^3$ and 353.2 $m^3$, respectively). In contrast, average stem density (894 stems/ha) and average ground slope (17.3%)

were lower than at the daily machine-level (1093 trees/ha and 17.9% respectively). The ranges of all variables were narrower at the cutblock-level, indicating that aggregation of daily production reports reduced observed variability. Cut-block size, with a mean of 18.0 ha and an interquartile range of 18.3 ha, exhibited substantial variation. The relatively large standard deviation (16.6 ha) indicates considerable differences in cut-block sizes across the dataset.

### 6.3.1 Primary Analysis: Using Daily-Level Repeated Measures per Machine

A mixed-effects model was first fit with MachineId nested within BlockId as random intercepts, assuming constant residual variance. The fixed effects were average stem size, average volume per hectare, average stem density, and average ground slope. Table 6.3 shows the estimated coefficients, SE, and 95 % CIs for each fixed effect.

*Table 6.3 Estimated coefficients, SE, CI, and p-values for each fixed effect in the homoscedastic daily machine-level model.*

| Variable | Coefficient | SE | CI lower boundary | CI upper boundary |
|---|---|---|---|---|
| Avg. stem size | 60.05 | 4.31 | 51.05 | 68.49 |
| Avg. volume per ha | 0.070 | 0.006 | 0.058 | 0.082 |
| Avg. stem density | 0.011 | 0.001 | 0.008 | 0.014 |
| Avg. ground slope | -0.49 | 0.06 | -0.61 | -0.39 |

Average stem size exhibited a strong positive effect on productivity (60.05; CI: 51.05, 68.49), whereas average volume per hectare (0.070; CI: 0.058, 0.082) and average stem density (0.011; CI: 0.008, 0.014) had smaller positive coefficient. However, average volume per hectare and stem density have much larger range in units than average stem size, making direct comparisons of coefficient magnitudes less meaningful. In contrast, average ground slope (-0.52; CI: -0.62, -0.42) had a negative impact on productivity. Regarding random-effects variation, the largest variance component was observed between cutblocks (SD 20.99), followed by between-machine variation (SD 10.44), and within-machine residual variation (SD 16.28).

A second model relaxed the assumption of constant residual variance by specifying a varIdent structure to account for machine-specific residual variances. Table 6.4 summarizes the fixed-effect estimates under this heteroscedastic approach, which are generally consistent with the homoscedastic model but differ slightly in magnitude. While average stem size showed a somewhat stronger positive effect (67.99), its confidence interval (CI: 59.42, 76.56) and standard error (4.37) remained nearly unchanged. The coefficient for average volume per hectare increased by 0.011, representing a relatively larger shift compared to the 0.03 decrease in the coefficient of average ground slope, particularly given the differences in their respective unit scales. The positive effect of average stem density remained largely unchanged (0.012; CI: 0.010, 0.015).

*Table 6.4 Estimated coefficients, SE, CI, and p-values for each fixed effect in the heteroscedastic daily machine-level model.*

| Variable | Coefficient | SE | CI lower boundary | CI upper boundary |
|---|---|---|---|---|
| Avg. stem size | 67.99 | 4.37 | 59.42 | 76.56 |
| Avg. volume per ha | 0.059 | 0.006 | 0.047 | 0.059 |
| Avg. stem density | 0.012 | 0.001 | 0.010 | 0.015 |
| Avg. ground slope | -0.46 | 0.045 | -0.46 | -0.37 |

The cutblock SD remained the largest source of variability (SD = 19.41), followed by machine variation (SD = 9.93), with a notably higher residual variation (SD = 33.91) compared to the homoscedasticmodel. The varIdent structure in the heteroscedastic model further indicated that some machines exhibit considerably higher or lower residual variance than others, with values ranging from 0.05 to 1.00 (Appendix C.2.3).

Figure 6.2 shows the residuals of the homoscedastic and heteroscedastic models plotted against the fitted values.

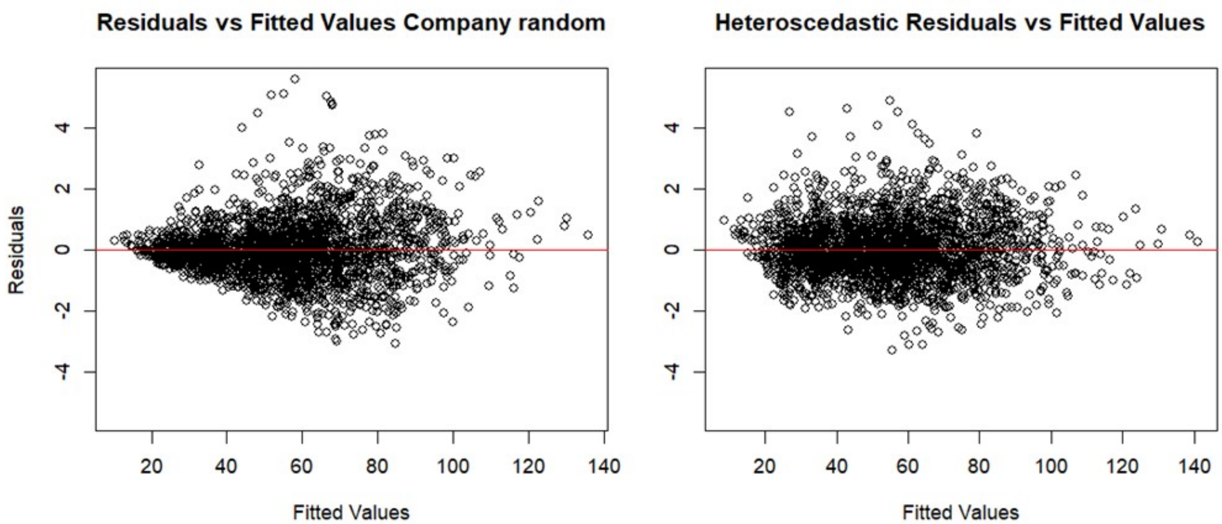


*Figure 6.2 Residuals of the homoscedastic and heteroscedastic daily machine-level models plotted against the fitted values.*

Overall, the homoscedastic residuals appear to be centered around zero across the range of fitted values, with roughly even dispersion on either side of the horizontal line. However, a slight increase in residual spread as fitted values increase (funnel shape) suggests potential heteroscedasticity. While this pattern indicates some violation of the homoscedasticity assumption, it does not appear to be severe. In contrast, the heteroscedastic model better accounts for variability, as its residuals remain centered around zero with a more stable spread, despite a few outliers at higher fitted values. This suggests that adjusting for heteroscedasticity effectively captures underlying variation. Additionally, although the heteroscedastic model yields lower marginal and conditional $R^2$ values ($R^2m = 0.1888$; $R^2c = 0.4261$) compared to the homoscedastic model ($R^2m = 0.3149$; $R^2c = 0.7772$), it offers a more appropriate fit by explicitly modeling non-constant variance in the data. The improved model fit is further supported by information criteria, where the heteroscedastic model achieves a lower AIC (25,982) and BIC (26,446) compared to the homoscedastic model (AIC = 26,694; BIC = 26,736), indicating a better balance between model complexity and explanatory power.

### 6.3.2 Secondary Analysis: Using Aggregated Cutblock-Level Data

A simplified model was fit at the cutblock-level, using a single aggregated record per cutblock. Because there is no replication within each cutblock, nested random effects could not be estimated. Instead, a standard linear model was applied, including average stem size, average volume per hectare, average stem density, and average ground slope, along with cutblock size as an additional fixed effect (Table 6.5).

*Table 6.5 Estimated coefficients, SE, CI, and p-values for each predictor variable in the linear cutblock-level model.*

| **Variable** | **Coefficient** | **SE** | **CI lower boundary** | **CI upper boundary** |
|---|---|---|---|---|
| Avg. stem size | 61.02 | 2.24 | 56.63 | 65.41 |
| Avg. volume per ha | 0.052 | 0.004 | 0.043 | 0.061 |
| Avg. stem density | 0.014 | 0.001 | 0.012 | 0.015 |
| Avg. ground slope | -0.24 | 0.05 | -0.34 | -0.15 |
| Cutblock size | 0.001 | 0.005 | -0.009 | 0.012 |

Average stem size, average volume per hectare, and average stem density exhibited positive effects on productivity, with coefficients similar in magnitude to those observed at the daily machine level (61.02; CI: 56.63, 65.41, 0.052; CI: 0.043, 0.061, and 0.014; CI: 0.012, 0.015, respectively). The negative effect of average ground slope persisted but was less pronounced (-0.24; CI: -0.34, -0.15). Cutblock size had a coefficient near zero (0.001; CI: -0.009, 0.012), suggesting it may have a negligible influence on productivity, as its CI includes zero.

The narrower CIs indicate greater precision in the estimated effects at the cut-block level compared to the daily machine level. This suggests that aggregation at the cut-block scale reduces variability, likely because short-term fluctuations in machine performance and environmental conditions average out over larger spatial and temporal scales.

Finally, a mixed-fixed effects model was fit for the cutblock-analysis, including contractor as a random effect, in order to account for potential heteroscedasticity. The contractor-specific varIdent argument allowed for residual variances in contractor (Table 6.6).

*Table 6.6 Estimated coefficients, SE, CI, and p-values for each fixed effect in the heteroscedastic cutblock-level model.*

| Variable | Coefficient | SE | CI lower boundary | CI upper boundary |
|---|---|---|---|---|
| Avg. stem size | 57.08 | 3.04 | 51.12 | 63.04 |
| Avg. volume per ha | 0.031 | 0.005 | 0.022 | 0.040 |
| Avg. stem density | 0.003 | 0.001 | 0.001 | 0.006 |
| Avg. ground slope | -0.36 | 0.04 | -0.45 | -0.28 |
| Block size | 0.013 | 0.005 | 0.004 | 0.022 |

The positive effect of average stem size was slightly smaller (57.08; CI: 51.12, 63.04) compared to the standard linear model. However, the positive effects of average volume per hectare (0.031; CI: 0.022, 0.040) and average stem density (0.003; CI: 0.001, 0.006) were considerably smaller, particularly given their respective unit scales. In contrast, the negative effect of average ground slope was more pronounced (-0.36; CI: -0.45, -0.28). The positive effect of block size (0.013; CI: 0.004, 0.022) was statistically significant, but its magnitude remained comparatively small. Overall, these estimates are largely consistent with those from the standard linear model. However, the lme approach accounted for an additional source of variation at the contractor level (SD = 33.49) alongside a residual standard deviation of 25.27.

Figure 6.3 shows the residuals of the cutblock-level linear and the heteroscedastic model plotted against the fitted values.

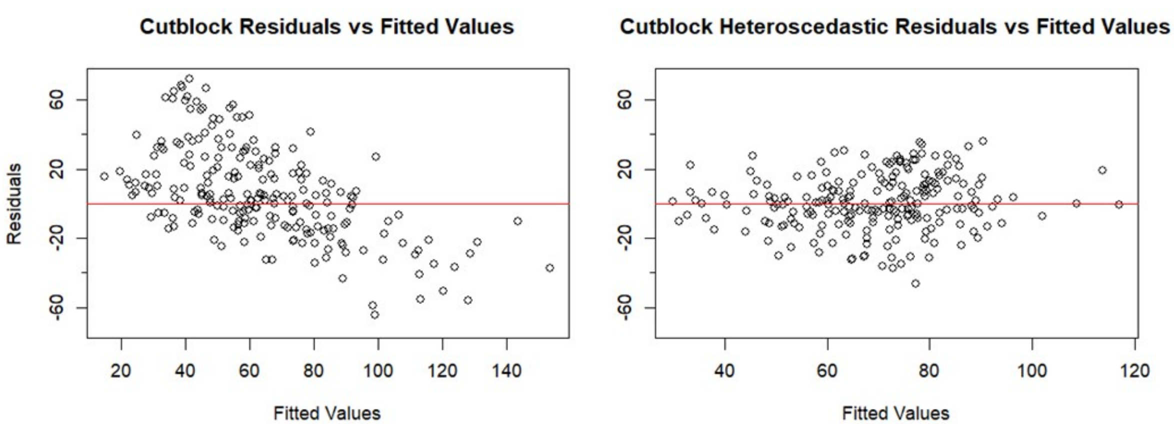


*Figure 6.3 Residuals of the homoscedastic and heteroscedastic cutblock-level models plotted against the fitted values.*

The residuals of the standard linear model exhibited uneven spread across the range of fitted values, with substantial variance at both lower and higher fitted values. While the overall spread appears wider for smaller fitted values, this may be due to the greater frequency of observations in this range. Additionally, residuals tend to shift negatively as fitted values increase, suggesting a potential systematic bias in the model. The heteroscedastic model allowed for different variance estimates across contractors, leading to a more stable residual spread across the range of fitted values. As shown in Figure 6.3, the residuals of the heteroscedastic model display a more consistent variance, supporting the appropriateness of this adjustment.

The heteroscedastic model demonstrated a better fit under AIC (1841 compared to 1913 for the standard linear model), indicating that accounting for variance heterogeneity improves model performance. However, BIC (1960 compared to 1933) favored the simpler linear model due to its stricter penalization of model complexity. Additionally, the standard linear model generated a multiple $R^2$ of 0.888, suggesting a high proportion of variance explained by the fixed effects. In contrast, the heteroscedastic model produced a $R^2m = 0.509$ and a $R^2c = 0.806$. While the standard linear model achieved higher $R^2$ values, the heteroscedastic model provided a more reliable fit by explicitly modeling the variance heterogeneity across contractors.

To illustrate the influence of the fixed variables on productivity, Figure 6.4 shows the estimated marginal means of productivity as a function of average stem size, average volume per hectare, average stem density and average ground slope at both the daily machine-level and cutblock-level.

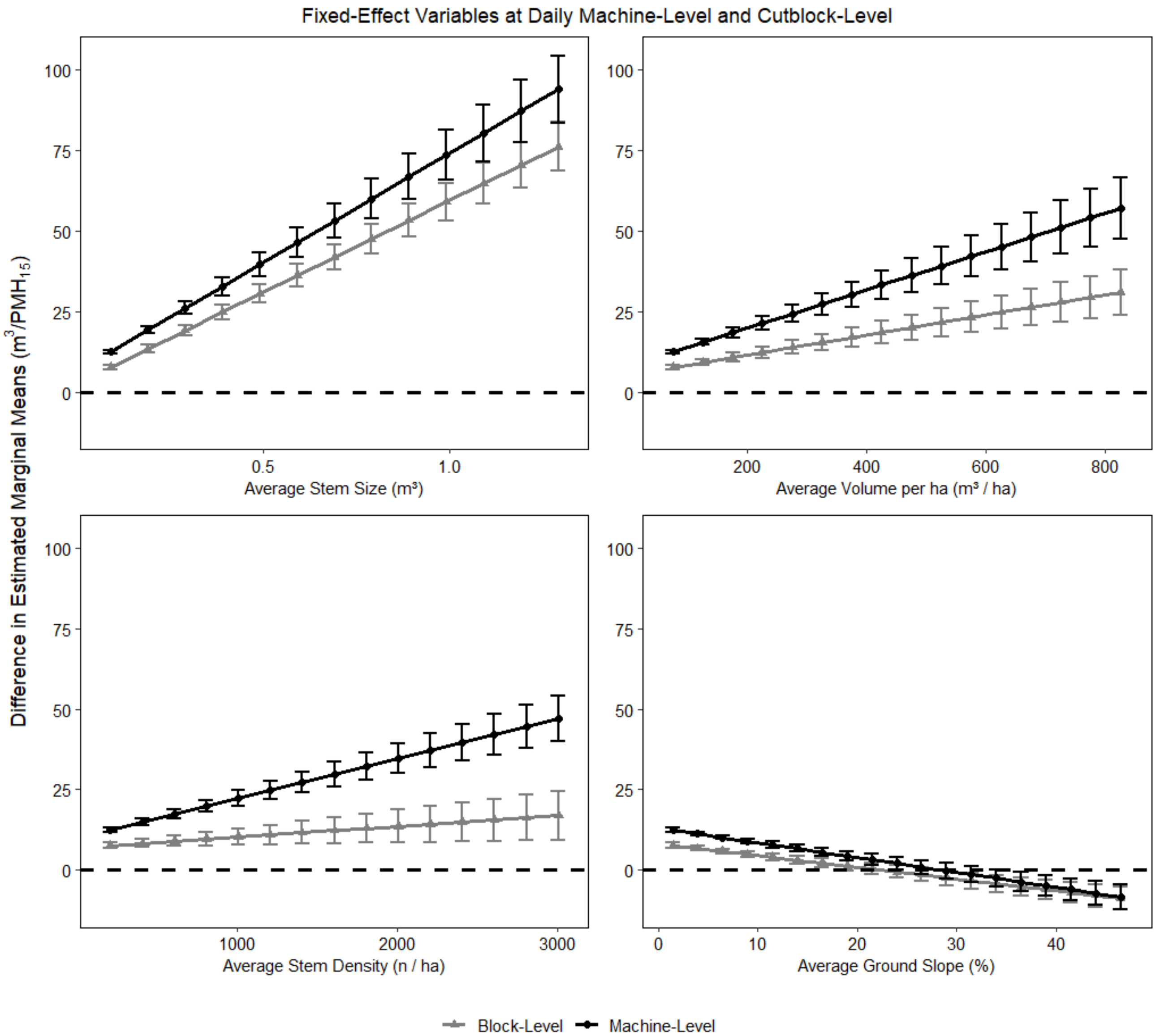


*Figure 6.4 Estimated marginal means of productivity as a function of average stem size, average volume per hectare, average stem density and average ground slope at both the daily machine-level and cutblock-level. Dashed horizontal line at zero represents the baseline, while the solid black and gray error bars indicate confidence intervals for daily machine-level (machine-level) and cutblock-level (block-level) respectively..*

Across all variables, productivity estimates at the cutblock-level are lower than at the daily machine-level. While the general trends remain consistent between the two levels, notable differences can be observed in the magnitude of slopes. The effect of average stem size is particularly pronounced, showing the highest productivity increase with increasing stem size at both scales. However, larger differences are observed for average stem density and average volume per hectare, where the slopes at the daily machine-level are noticeably steeper, indicating a stronger increase in productivity with increasing values compared to the cutblock-level. In contrast, the effect of average ground slope shows the smallest difference between levels. While productivity declines as ground slope increases at both levels, the magnitude of this decrease is nearly identical. At both levels, the model estimates productivity values below zero at higher ground slopes.

Figure 6.5 presents the estimated marginal means for cutblock size, a fixed-effect variable that was exclusively modeled at the cutblock-level.

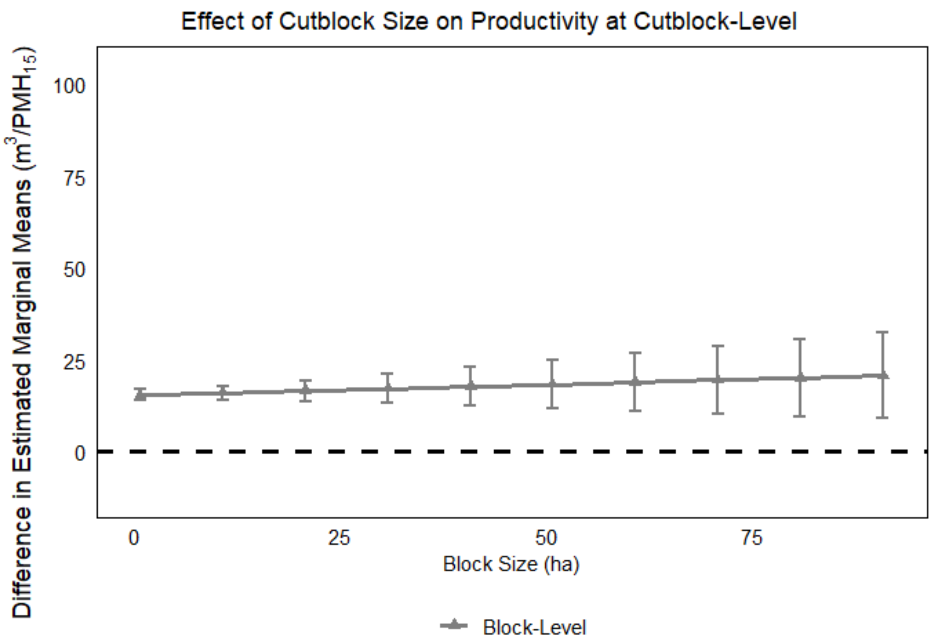


*Figure 6.5 Estimated marginal means for cutblock size at the cutblock-level (block-level). Dashed horizontal line at zero represents the baseline, while the dashed error bar indicates confidence intervals.*

A slight positive relationship between cutblock size and productivity was noticed. However, the slope of this effect remains relatively shallow, suggesting that cutblock size has only a limited influence on productivity. The CIs widen at larger block sizes, indicating increased uncertainty in these estimates due to fewer observations at the upper range of cutblock sizes.

## 6.4 Discussion

A fundamental innovation of this study lies in the use of a large, standardized dataset to analyze long-term productivity of WT harvesting operations. While many previous studies rely on data that are either small in scope or aggregated from multiple, non-standardized sources, the FMC Module provided a uniform method of production and terrain data collection from diverse operating conditions. This dataset is continuously updated with daily production reports and, therefore, is constantly growing. Furthermore, it captures data at an unprecedented spatial and temporal scale. Due to its continuous expansion, the derived analyses can be regularly updated and refined.

A key methodological decision in the analysis of this dataset involved whether to model machines and cutblocks as crossed or nested random effects. Machines and cutblocks were treated as partially crossed random effects, as some machines operated in only one cutblock, while others were present in multiple cutblocks. Ideally, in a fully crossed design, each machine would operate across multiple cutblocks, with a roughly equal number of cutblocks assigned to each machine to ensure a balanced design. Nested random effects imply that each cutblock has its own distinct set of machines, and in such designs, machine IDs typically range from 1 to the total number of machines within each cutblock. In partially crossed designs, like the one in this study, potential challenges can arise:

- If incorrectly nested, instances of the same machine operating in multiple cutblocks may be counted as separate machine identities, inflating cutblock-level variance and skewing test statistics.
- Conversely, incorrectly crossing when the same machine identifier is not truly the same physical machine (or if repeated uses are too sparse) risks pooling data that should remain distinct, leading to misestimation of random effects.

In the case of partially crossed random effects, as is the case in this dataset, some software (e.g., nlme and glmmTMB) exhibited convergence issues when estimating machines and blocks as crossed effects. While lme4 is more flexible in estimating models with partially crossed effects, it does not support fitting heteroscedastic residual variance structures. Consequently, nlme was selected for its capacity to handle heteroscedastic mixed-effects models, within random effects for machines nested within cutblocks, an approach that generally performed well despite potential slight misestimation.

Another major challenge was addressing heteroscedasticity. Given the practical reality that individual machines (and potentially operators) can vary in their within-machine consistency, a variance structure was specified using varIdent(MachineId), allowing the model to estimate distinct residual variances for each machine. This approach relaxed the assumption of homoscedasticity by permitting residual variances to differ across machines rather than assuming constant variance across all observations. Incorporating machine-specific variance estimates improved model fit and better captured productivity variability.

While this choice introduced additional variance parameters and increased the risk of overfitting - particularly for machines with limited observations - it significantly improved model fit, as indicated by reductions in AIC and BIC, and resulted in more randomized residual patterns. Alternative variance structures, such as varPower or data transformations, could have further refined the model or simplified the parameter set. However, varIdent was chosen to maintain interpretability. Moreover, the inclusion of MachineId both as a random effect and within the varIdent structure underscores an important modeling consideration: the random intercept accounts for between-machine variability, while the machine-specific residual variance structure captures within-machine heteroscedasticity, highlighting the complexity of variance partitioning in the dataset. To assess the potential overfitting introduced by machines with very few observations, a sensitivity analysis was conducted by excluding machines with fewer than 10 observations. The results showed only a marginal improvement in AIC (24,672 vs. 25,982) and BIC (24,965 vs. 26,446) (Appendix C.2.3; C.2.4), suggesting that the primary model remained robust despite the inclusion of all machines.

Random slopes were deliberately excluded despite evidence (from spaghetti plots in Appendix C.2.1) that specific machines might have different productivity trends. Implementing random slopes would require more complex correlation structures (e.g., pdBlocked or pdMat), likely leading to interpretation challenges, especially under an exploratory analysis. In addition, the data constraints (e.g., limited repeated observations for certain machines) reduce confidence in estimating parameters reliably. The final model thus balances interpretability with capturing the most critical sources of variability.

Another methodological advancement is the systematic process of selecting suitable cutblocks and filtering out incomplete or potentially erroneous production data. By establishing clear coverage thresholds (e.g., minimum cutblock completion percentages and acceptable levels of GNSS error), the study ensures that the data used for modeling is of consistently high quality. This approach could be adopted by other organizations seeking to leverage daily production reports from partial or gradually expanding datasets.

In line with many short-term studies that analysed productivity of individual machines in specific contexts, this study demonstrates that average stem size, average volume per hectare, average stem density, and slope percent remain key drivers of feller buncher productivity across diverse operations. The benefit of having a very large data set is that a model can be generalized for BC conditions (e.g., different terrain, climate, or species composition) within the range of observations.

Stem size showed a strong, consistently positive association with productivity in all models. This aligns with previous findings, reported in Chapter 3, that stated that larger trees processed per cycle result in higher output per unit time. Average volume per hectare showed a moderate positive effect on productivity. However, this effect is weaker than that of stem size, indicating that total volume alone is not as strong a driver of productivity as individual piece size. Similarly, stem density had a small positive effect on productivity at both the daily machine-level and the cutblock-level which suggests that in areas with higher stem densities per hectare, machine efficiency may improve due to closer spacing between trees, reducing boom movement and repositioning time. In contrast, productivity declines with increasing slope, and when other factors are held at their minimum, is predicted to become negative. As a negative production is unrealistic, this pattern is likely the result of a linear model being applied to a non-linear relationship. While slope does reduce productivity due to increased machine travel time, positioning challenges, and reduced boom efficiency, the actual rate of decline is unlikely to remain constant beyond a certain point. Instead, a diminishing returns effect is more plausible, where productivity decreases at first but levels off at hifher values. Cutblock size, which was only included in the cutblock-level model, had a small but positive effect on productivity. This suggests that larger cutblocks may enable better layout planning and machine movement optimization, enhancing productivity over extended harvesting periods. However, the relatively minor effect size indicates that cutblock size alone does not strongly dictate productivity.

While p-values for the individual fixed variables were reported and included in the Appendix C, this study prioritizes practical significance over strict statistical inference, focusing on the magnitude and direction of effects rather than binary significance thresholds. Mixed-effects models, particularly in an exploratory context, pose challenges for traditional statistical tests due to their reliance on distributional assumptions. By using CIs to assess effect sizes, this study aimed to provide a more transparent and interpretable approach to understanding productivity drivers. Given that forestry data often exhibit variability across machines and cutblocks, this approach supports more nuanced understanding of operational performance.

Assessing model residuals provides insights into the suitability of homoscedastic and heteroscedastic approaches for analyzing feller buncher productivity. The homoscedastic models' residuals at daily machine- and cutblock-level suggested the presence of heteroscedasticity, violating the assumption of constant variance. While this deviation is not extreme, it highlighted the potential need for a model that explicitly accounts for variance heterogeneity. The heteroscedastic models addressed this by allowing residual variance to vary across groups, leading to a more stable residual spread with fewer patterns of systematic bias. Despite some outliers at higher fitted values, this improved variance structure suggests that heteroscedastic modeling more accurately captures underlying variation in machine- and contractor-level differences. Model selection criteria further support the heteroscedastic model's improved fit at the daily machine-level, with lower AIC (25,982 vs. 26,694) and BIC (26,446 vs. 26,736), indicating a better balance between complexity and fit. At the cutblock-level, the heteroscedastic model also shows a lower AIC (1841 vs. 1913), while the standard linear model exhibits a lower BIC (1960 vs. 1933), likely due to BIC's stricter penalization of model complexity. This suggests that while the heteroscedastic model better accounts for variability, its added parameters make it less favorable under BIC's criteria.

The interpretation of $R^2$values further highlights differences in model explanatory power. At the daily machine-level, the homoscedastic model exhibited higher $R^2$m (0.3149) and $R^2$c (0.7772) compared to the heteroscedastic model ($R^2$m = 0.1888, $R^2$c = 0.4261). While these values suggest that the homoscedastic model explains a greater proportion of variance, they may overestimate explanatory power by failing to account for non-constant variance. The heteroscedastic model's lower $R^2$ values arguably provide a more conservative and realistic estimate of explained variance, aligning with its improved residual distribution. The fact that random effects explain such a large proportion of variance suggests that additional explanatory variables may need to be captured to improve model performance. A similar pattern was observed at the cutblock-level, where the standard linear model produced a multiple $R^2$ of 0.888 and an adjusted $R^2$ of 0.8852, whereas the heteroscedastic model resulted in $R^2$m = 0.509 and $R^2$c = 0.806. This suggests that while the standard model appears to explain more variation, it does not properly account for differences in residual spread across contractors, potentially inflating its explanatory power. Furthermore, the results of Chapter 5 suggested that estimations become more reliable at an aggregated level, indicating that the cutblock-level analysis may provide greater accuracy.

A limitation of this study was the availability of data. Despite the extensive initial dataset of over 9,800 reports, incomplete cutblock data and possible GNSS errors necessitated systematic filtering, reducing the final sample. However, this limitation promises to disappear as soon as contractors have all of their machines equipped with OBCs for consistent recording. Data could theoretically be incorporated in productivity modeling instantly unless GNSS recording errors occur. Moreover, only three main predictors - stem size, stem density, and ground slope - were consistently available across all observations. Other potentially relevant factors (e.g., operator ID, machine class, weather, or detailed terrain attributes) were either only partially collected or not yet standardized in their recording method and could have improved the fit of the model. Future expansions of the dataset to include more detailed operational and environmental factors may help address the unexplained heteroscedasticity, particularly at extreme productivity values (right-tail phenomena).

Another limitation of the study is the linear modeling approach, which assumes a continuous and unbounded relationship between ground slope and productivity. Since feller bunchers can still operate on slopes up to 40%, the predicted negative productivity values at higher slopes suggest that the model is over-extrapolating the trend rather than accurately capturing operational limits. In reality, productivity would decrease toward zero rather than becoming negative, as trees and harvested volume cannot be lost. This mathematical artifact highlights the limitations of linear regression in representing non-linear relationships, particularly for slope effects, which may exhibit threshold dynamics where productivity stabilizes at low values rather than declining indefinitely. A more flexible non-linear model incorporating interaction terms could better capture the diminishing returns of increasing slope.

Additionally, while steeper slopes generally reduce productivity by increasing machine travel and positioning time and limiting effective boom reach, previous studies on winch-assist feller directors, as shown in Chapter 3, did not observe the same degree of productivity loss. This suggests that winch-assist systems may mitigate some of the negative effects of slope on productivity. However, the lack of explicit differentiation between conventional and winch-assisted feller buncher operations in this study presents another limitation. As the dataset expands, incorporating this distinction could improve the model's applicability across a broader range of harvesting conditions.

This study is primarily exploratory rather than predictive, as it is limited by the availability of standardized variables and the inherent complexity of operational forestry data. Rather than aiming to develop a strict forecasting model, the focus was placed on identifying key productivity drivers, quantifying their relative effects, and defining a modeling framework. While the current models effectively capture the relationships between fixed-effect variables and productivity, they are not structured for precise output prediction under specific conditions. Instead, they provide a generalized understanding of productivity trends across diverse operating environments. These results represent a significant improvement over how FPDat II data have been used in the industry up to this point. Previously, productivity evaluations relied on manual data input and the delineation of covered areas, while average produced volumes were typically recorded in the field. Furthermore, as the dataset continues to grow, incorporating additional environmental variables and a detailed machine classification, future research could refine these models to offer more context-specific productivity estimates. Expanding the dataset would allow for more granular modeling tailored to particular conditions, such as regional differences, stand composition, or terrain challenges, ultimately improving the applicability of productivity assessments for industry decision-making.

From a practical standpoint, the capacity to detect machine-specific variance has direct implications for fleet management. Operators and contractors can investigate machines showing especially high variance, diagnosing issues related to operator training, mechanical maintenance, or mismatches with site conditions. Although the current approach does not prioritize prediction per se, the underlying parameter estimates could inform near-real-time decision-support tools - especially as more standardized data accumulates, further improving model robustness.

In summary, this study underscores the value of standardized, large-scale production data for understanding and modeling WT harvesting productivity. While some methodological and data-collection challenges remain - particularly around partial crossing, machine labeling, and underdefined operational contexts - the heteroscedastic mixed-effects framework provides a strong foundation for ongoing improvements.

## 6.5 Conclusion

This study demonstrates the potential of long-term, standardized production data to shed light on the drivers of WT harvesting productivity. By using a mixed-effects framework that accounts for machine- and cutblock-level variability, and by allowing machine-specific residual variances (heteroscedasticity), the models confirm average stem size, average volume per hectare, average stem density, and average ground slope as key factors influencing daily machine- and cutblock-level productivity. The methodological choices - particularly regarding nested vs. crossed random effects - illustrate the complexity of large, partially imbalanced datasets.

Beyond modeling, this research highlights the value of the FMC Module as a first-of-its-kind tool for remote production analysis in WT harvesting operations. Currently, users can retrieve daily production reports at the cutblock-level or examine specific daily machine-level details, enabling ongoing comparisons against expected volumes from inventory data. As data collection becomes more comprehensive, especially when all contractor machines are consistently equipped with FPDat II on-board computers, the ability to integrate the mixed-effects modeling approach presented here into the FMC Module (or a similar platform) could provide near-real-time guidance on likely productivity under changing site conditions. Such integration would further empower operators, planners, and decision-makers to manage harvesting operations dynamically, refining equipment allocation and operational strategies in response to actual performance data. Ultimately, this blend of big-data analytics and cloud-based production monitoring points toward a more data-driven, adaptable, and efficient future for timber harvesting in BC and beyond.

# Chapter 7 - Conclusion

## 7.1 Dissertation Objectives

The primary objective of this dissertation was to develop methods for automated productivity analysis of ground-based WT felling machines by integrating OBC data with inventory data and exploring the effects of key productivity influencing variables on WT felling. These objectives were achieved by addressing the research questions outlined below.

**Q1: Which are the key variables influencing the productivity of WT felling machines?**

**Approach:** To gather relevant knowledge and establish a substantial database on productivity measurement, rates, and influencing factors of WT felling machines, Chapter 3 systematically synthesized existing research. It compiled and analyzed evidence from productivity studies on feller bunchers and feller directors. The systematic approach ensured a comprehensive search and selection of relevant evidence by applying the same search criteria to 11 bibliographic databases, search engines, and forest operations-specific online libraries. The process involved an initial screening of titles and abstracts to identify retrievable and relevant evidence based on predefined exclusion criteria. A subsequent full-text analysis refined the selection, and systematic data extraction enabled the development of a structured database on productivity studies of feller bunchers and feller directors.

**Key Finding:** The knowledge database indicates that most previous research on production of WT felling operations was conducted in North America. The majority of the findings were technical reports published by a Canadian research institution. It was also found that a considerable portion of the literature lacked statistical analysis, particularly the technical reports. Piece size, ground slope, and silvicultural treatment were the most commonly studied factors influencing productivity. While a general understanding of the key factors affecting feller buncher and feller director productivity already exists, the lack of automated, standardized data collection methods remains a significant challenge. Furthermore, logical frameworks and analytical procedures must be developed to transform automatically collected data into meaningful production metrics. The study conducted in Chapter 3 highlights the need for further research to develop a system that utilizes OBC data for machine productivity analysis.

**Q2: How can machine production time metrics be accurately derived from data collected with commercially available data loggers?**

**Approach:** In the geographical context of the research in the dissertation, the most common and commercially available aftermarket OBC system was determined to be the FPDat II data logger. Despite their widespread use, a gap in the literature and industry knowledge remains regarding their efficacy and accuracy of production monitoring. To partially address this gap, the study in Chapter 4 developed an innovative protocol to estimate direct work time and productive time, utilizing FPDat II ignition and motion data, and validated its performance. The accuracy of these estimates was assessed by comparing over 400 h of direct timing through field observations with remotely collected ignition and motion data of 11 different machines. The study further identified data processing strategies to minimize errors in these estimates. The errors were quantified for work time and productive time in terms of absolute and relative values, the MAE, the RMSE, and the CV(RMSE), followed by a statistical analysis.

**Key Findings:** The study conducted in Chapter 4 represents the first comprehensive effort to develop, document, and validate automated time analysis for a wide range of WT ground-based forest machinery using FPDat II data loggers. Although the results showed limited accuracy in the estimation of direct work time ($PMH_0$), the inclusion of time thresholds in the analysis of ignition and motion data enabled a reduction of the overall productive time ($PMH_{15}$) error to less than 1%. Sensitivity analyses identified WTD at 60 and 90 seconds, with the inclusion of OTD, to be the optimal thresholds across all machine types and for feller bunchers specifically, respectively. These thresholds effectively minimized overestimation caused by idle events or short ignition-off periods within delays. Despite this, the ability to successfully track productive time of ground-based timber harvesting equipment, including feller bunchers in WT operations, opens up further opportunities for the development of fully automated productivity analysis solutions.

**Q3: How effectively and consistently can key production metrics be automatically estimated for WT felling machines using data loggers integrated with forest inventory data?**

**Approach:** By integrating ignition status, motion status, and machine location data from FPDat II data loggers with LiDAR forest inventory data, the research of Chapter 5 aimed to accurately predict key production metrics such as productive time, area covered, volume harvested, and overall productivity on a daily basis and over longer cumulative periods for individual machines. The efficacy of this fully automated data collection and analysis approach was tested using a direct comparison with in-field data collected through video recordings and drone imagery. Three feller bunchers were observed for a total of 106.3 hours, covering an area of 14.3 ha. The discrepancies between observed and estimated production metrics were quantified absolute and relative errors, the MAE, the RMSE, and the CV(RMSE).

**Key Findings:** The findings of Chapter 5 indicated minimal discrepancies in productive time recordings (0.9%) and area covered by machines (-1.9%), with slightly larger discrepancies observed in volume harvested (-4.4%) and productivity (-5.4%) at aggregated level of observation time. More significant disparities in area coverage estimations were noted during individual shifts, particularly when multiple machines operated simultaneously or when there was incomplete coverage of machine tracking by FPDat II data loggers. With its findings, this study showed to be crucial step towards understanding the capabilities and limitations of OBC data for remote production analysis in forest operations. While the approach for detecting the area covered is generally effective, refinements could enhance its accuracy and reliability.

**Q4: How can productivity models for WT felling machines be developed and improved using long-term production data from data loggers?**

**Approach:** Building on the functionality of the FMC Module and its standardized data collection from FPDat II data loggers, this study assembled a large dataset of production reports comprising diverse operating conditions across multiple cutblocks and machines. The reports were first analysed at the daily machine-level, capturing productivity, stem and volume density per hectare and ground slope. To account for variability across machines and blocks, mixed-effects models were then fitted using nlme in R. A homoscedastic model was initially tested, followed by a heteroscedastic variant that allowed machine-specific residual variances. This heteroscedastic approach addressed the practical reality of differing within-machine variability. Additionally, a cutblock-level analysis was performed by aggregating daily reports into a single observation per cut-block and adding cutblock size as a fixed-effect. Outlier and error filtering rules ensured consistent, high-quality observations by excluding incomplete blocks, GNSS errors, and extreme productivity values. The resulting final models were compared via likelihood-based criteria (AIC and BIC) and residual diagnostics to assess fit and interpretability. The detailed step-wise documentation provides a guidance for large-scale, long-term production data.

**Key Findings:** Through its modeling approach, this study demonstrated that feller buncher productivity is significantly influenced by stem size, volume per hectare, stem density, and slope across diverse operating conditions. More specifically, the findings reinforce stem size as the most critical factor, while volume per hectare and stem density also contribute positively, improving machine efficiency. Slope has a negative impact and cutblock size was found to have only a minor influence on productivity at the cutblock level.

By incorporating heteroscedasticity, the developed models better reflect variability in forest operations, where contractor differences, local stand and site conditions, and machine characteristics introduce unequal variance. The heteroscedastic models at both the daily machine and cutblock levels provided a more stable residual structure, capturing machine-specific and contractor-specific variability, respectively, and reducing the potential overestimation of explanatory power observed in the homoscedastic approach. These results highlight the importance of evaluating model assumptions beyond traditional goodness-of-fit measures, ensuring that findings are not only statistically sound but also operationally meaningful. While not currently designed for prediction, future dataset expansion could enable more refined, condition-specific productivity estimates, supporting real-time monitoring and data-driven operational decision-making.

## 7.2 Innovations

**Chapter 3:** This study introduces several innovations in understanding the methodologies and results in WT felling productivity measurement. It provides the first systematic synthesis of global evidence on feller buncher and feller director productivity, creating a metadata database of productivity-influencing factors categorized into site and stand-, and operation-related variables. The study identifies key explanatory variables for WT felling productivity, such as piece size, ground slope, and silvicultural treatments, while highlighting critical research gaps, including a lack of studies on large piece sizes, steep-slope operations, and the effects of snow cover. It emphasizes the need for standardized methodologies and accurate data collection tools to enable cross-study comparisons and improve productivity models. Additionally, the study provides practical insights into improving operations through better operator training, machine maintenance, and targeted silvicultural practices. By combining a systematic review, methodological advancements, and actionable recommendations, this study addresses existing gaps and lays the foundation for future research and operational improvements in WT felling.

**Chapter 4:** This study represents the first comprehensive attempt to develop, document, and validate automated time analysis protocols for WT ground-based forestry equipment using FPDat II OBC technology. The protocols leverage standardized time thresholds for data pre-processing - specifically Working-To-Delay (WTD) and Off-To-Delay (OTD) - to optimize the estimation of work time and productive time. Validation was conducted through extensive field data collection, filling a critical gap in the understanding of OBC accuracy. The inclusion of these time thresholds improved the accuracy of time metric measurement, especially for productive time, effectively minimizing overestimation caused by idle events and short ignition-off periods.

The approach is not limited to FPDat II technology and can be broadly applied to other systems relying on similar principles, making it universally adaptable to forest operations globally. Moreover, the study laid the groundwork for integrating productive time data with zonal statistics and volume extrapolation, enabling near-real-time productivity monitoring and performance analysis. This integration has the potential to support continuous monitoring, benchmarking, and improved tactical and strategic planning.

**Chapter5:** This study introduced a fully automated production analysis using FPDat II data, representing the first systematic application of this technology for monitoring feller buncher operations in WT harvesting beyond estimating time metric. It developed a systematic buffering approach for GNSS machine tracks to delineate harvested areas, integrating zonal statistics from forest inventory data to estimate harvested volume and productivity. Field validation confirmed its reliability, particularly at the cutblock-level, with minimal discrepancies in productive time estimation and manageable errors in area covered, volume harvested, and productivity. The sources of discrepancies - particularly at day-level granularity - were identified and solutions such as optimizing GNSS recording and excluding compromised data to enhance accuracy were proposed.

By providing daily machine-level productivity insights beyond traditional cutblock-level analysis, the research supports improved resource allocation, operational planning, and long-term benchmarking. Furthermore, it sets the stage for developing productivity models tailored to diverse harvesting operations and forest conditions, leveraging a growing database of automated production information.

**Chapter 6:** This study leveraged a large, standardized dataset of WT harvesting production reports and integrated cloud-based data collection from the FMC Module into advanced mixed-effects modeling for a wide range of forest operations. By allowing machine-specific and contractor-specific variability in residual estimates, the research addressed differences in operational performance between machines, moving beyond conventional assumptions of uniform variance. This innovative approach improved model fit and provided a more realistic representation of productivity variation in large, partially imbalanced datasets.

Additionally, the study presents a comprehensive methodological workflow that includes guidelines for excluding incomplete blocks resulting from missing data or GNSS errors that compromise area coverage. By analyzing productivity at both the machine-level (daily observations) and the cutblock-level (aggregated data), the research offered a hierarchical perspective on how stem size, volume and stem density, slope, and cutblock size influenced WT felling operations. Coupled with the FMC Module's near-real-time capabilities, this methodology laid the foundation for data-driven, adaptive forestry practices that could respond more dynamically to evolving site conditions and operational demands.

## 7.3 Limitations

**Chapter 3:** This study acknowledges several limitations that may affect the generalizability and applicability of its findings. The analysis was limited to English-language sources, which may have excluded relevant studies. Expanding the scope to incorporate research in other languages could have broadened the available evidence. Furthermore, the publications included in this chapter did not consistently report standardized units, making direct comparisons or statistical analysis challenging. Variations in data collection methodologies and a lack of transparency or missing information in some studies further complicated direct comparisons. These challenges in comparing and analyzing productivity values across previous studies highlight the need for more standardized, transparent, and comprehensive approaches in future research to enhance the reliability and comparability of productivity studies in forest operations.

**Chapter 4:** Due to its reliance solely on ignition and motion sensors, the approach introduced in Chapter 4 cannot distinguish between productive and non-productive movements or separate different work elements (e.g., loading vs. processing). Additionally, the 24-hour analysis window can split overnight shifts into two parts if they cross midnight, complicating the alignment of actual work activities with shift boundaries. While utilizing operator-independent data is a key strength of this study, it also prevented the use of direct operator inputs to pre-set tablet buttons. Such inputs would have enabled automatic discrimination among different operators or shifts, as well as the identification of activity/stop codes describing the reasons for delays or specific work tasks. Despite hundreds of hours of monitoring, the analysis was conducted at the daily-summary level, resulting in only 41 observations and limiting the statistical robustness.

**Chapter 5:** A significant constraint in this study was the incomplete coverage of machines, as not all feller bunchers in the same cutblocks were equipped with FPDat II units, leading to potential inaccuracies in estimated metrics such as area covered, volume harvested, and productivity. This issue can be aggravated when multiple machines work closely together - particularly if some lack data logger units - since the automated system may incorrectly attribute area covered. In addition, only ten observation days were available, limiting the statistical robustness of the findings. Challenges arose from the, by default low, GNSS recording frequency of FPDat II units, which can produce coarse spatial resolution and yield under- or overestimation of actual harvesting activities. The approach also assumes that any point within the “boom reach” plus an added buffer is felled if a machine passes nearby, potentially introducing errors when machines merely circle patches of standing timber without actually felling it. Finally, harvested volume estimates depend on inventory data and scaled volume; any discrepancies between inventory assumptions and actual harvesting can amplify uncertainty, particularly when reconciling daily estimates before scaled data become available.

**Chapter 6:** This study encountered several limitations that shaped its findings and potential applicability. First, only five explanatory variables (stem size, volume per hectare, stem density, slope and cutblock size) were consistently available in the dataset, excluding other key factors identified in Chapter 3 (e.g., ground roughness, operator ID, machine class, weather) that might have further explained productivity differences. In addition, data filtering to remove incomplete blocks, outliers, and GNSS errors reduced the original pool of 9,800+ reports to 3,081, potentially discarding partial yet valid observations and restricting generalizability.

Partially crossed random effects introduced modeling constraints, while heteroscedastic variance structures increased model complexity. Moreover, random slopes were intentionally omitted, even though the data suggested variable productivity trends among machines. This decision was made due to the complexity of additional correlation structures and limited repeated observations for certain machines, which could have led to unreliable parameter estimates. Additionally, the study did not include winch-assist operations, potentially overlooking key interactions that may influence productivity trends on steeper slopes.

## 7.4 Future Research

Future research should focus on enhancing the automated data collection and production analysis of feller bunchers achieved through the FMC project and extending it to all different types of machines employed for WT harvesting operations. Key challenges in data collection, quality assurance, and predictive modeling for the tree-to-truck forest supply chain should be addressed. The following areas will guide future work:

### 7.4.1 Enhancing Data Collection

Future research should prioritize improving the accuracy, completeness, and scalability of automated data collection for WT harvesting operations. Several key areas require attention to refine data availability, optimize area coverage estimation, and ensure the robustness of productivity models across diverse operational conditions.

A crucial enhancement involves expanding the range of explanatory variables to include operator ID, machine class, winch-assist time, weather conditions, ground roughness, and understory density. These factors could play a significant role in machine productivity but were not consistently available in the current dataset. For example, implementing a solution that automatically allocates weather variables - such as rainfall, snowfall, snow depth, and other environmental factors - into individual production reports, as proposed by Verret et al. (2021), could expand the available variables. Integrating such additional variables into productivity modeling could improve explanatory strength and provide a more comprehensive understanding of machine performance across different site conditions.

Another critical area for improvement in the automated data collection in this dissertation is the accuracy of area covered estimation, particularly at the day-level, where Chapter 5 identified higher errors compared to aggregated levels. One potential enhancement is to increase the recording frequency of FPDat II GNSS data points, which is currently set at a default threshold of 25 meters or 60 minutes for recording a new position. These thresholds may not adequately capture movements for all machine types, and felling machines in particular may require higher-resolution recording thresholds to improve delineation accuracy.

Building on this, future research can explore the impact of varying GNSS recording frequencies in combination with different buffer application logics to optimize area estimation across different machine types. Specifically, a systematic analysis of multiple combinations of buffer sizes and GNSS recording intervals should be conducted, based on high-frequency in-field GNSS recordings to simulate and assess the optimal configurations. The results have the potential to provide machine-type-specific recommendations for improving area coverage accuracy, enhancing the automated data collection's reliability, and refining productivity modeling.

To further enhance the data collection, effective work task detection and classification (activity recognition) models should be developed for various harvesting systems. By improving work task detection, the accuracy and resolution of time-related production metrics can be significantly enhanced. Machine learning models that integrate multiple data types - such as motion data, audio recordings, photographs, and video frames - could provide a robust solution for activity recognition. Motion data, combined with machine learning, has already proven effective for performance monitoring and activity recognition in forest operations and other industries (e.g., Borz, 2021; Zimbelman and Keefe, 2021; Borz et al., 2022). Additionally, incorporating sound data has demonstrated its potential in improving activity recognition for mechanized forest operations (Keefe et al., 2019; Becker and Keefe, 2022). Although machine learning-based activity recognition via photo/video analysis is still in its early stages in forestry, similar methods have been explored in the construction industry (Sherafat et al., 2020), and early-stage applications are under development in forestry at Lim Geomatics.

A missed opportunity in this research was the use of CAN bus data, which offers valuable potential for research in forest operations. The CAN bus system allows real-time access to internal machine parameters such as actuator movements, hydraulic pressures, flow rates, engine load, and operational states. This type of data can significantly enhance the granularity and accuracy of productivity analyses. Over the past two decades, several studies have demonstrated the value of CAN bus data for distinguishing work elements, monitoring trafficability, and identifying machine activities with high temporal precision (Suvinen and Saarilahti, 2006; Melander et al., 2020; Spencer and Torres, 2022; Torres et al., 2024). While this study did not incorporate CAN bus data, its integration could have added a deeper operational insight, particularly in identifying work elements and understanding machine dynamics across varying site conditions, potentially using machine learning algorithms. Future research should take advantage of FPDat II's capability to record this type of data.

Lastly, expanding the dataset to include a greater number of machines, companies, and geographic regions beyond BC is another priority. By increasing the scope of data collection across a wider range of operational conditions, future research can enhance model robustness and generalizability, ensuring that productivity estimates remain accurate across different terrain types, species compositions, and harvesting strategies.

### 7.4.2 Ensuring Data Quality and Integrity

To ensure the accuracy of productivity predictions and benchmarking, it is essential to develop an anomaly detection system capable of identifying and classifying errors in machine data, worklogs, and production metrics. This system should recognize and categorize discrepancies, inconsistencies, and implausible values in location and motion data, as well as in worklog geometries and production metrics. Statistical analysis and machine learning algorithms can be leveraged to detect deviations from expected patterns, providing an effective solution for error identification and correction.

Following the identification of anomalies and misclassifications, the criteria-based data cleansing system, as it was introduced in Chapter 6, should be expanded to assess the completeness, integrity, and reliability of production data and their associated features. This system would filter out issues, inconsistencies, and outliers, ensuring that only valid, high-quality data is retained. The outcome of this process would be a structured and reliable database of individual daily reports, with accurate production metrics and well-defined features for all tree-to-truck forest operations.

### 7.4.3 AI-Driven Predictive Modeling

The improvements in data collection, processing, and feature engineering, along with the implementation of data quality control and exclusion protocols, could enable the creation of a structured, high-resolution dataset capturing daily production metrics across the tree-to-truck forest supply chain. This dataset, potentially including hundreds of machines and cutblocks per day, provides a foundation for the development of predictive models aimed at forecasting key production metrics, such as productive time and overall productivity, for all forest operations within any given cutblock.

Another potential direction for future research is to validate the models using predictive analysis. While this study primarily focused on explanatory modeling, a future iteration could test the models against an independent dataset to assess their predictive accuracy in practical forest operations. This would provide stronger evidence for the practical utility of automated production modeling in forest operations.

Beyond traditional regression-based methods, developing machine-learning-based predictive models represents an opportunity to enhance productivity estimation under varying operational and environmental conditions. Advanced models could integrate non-linear relationships and high-dimensional interactions among variables, allowing for adaptive and real-time performance predictions. These models could be particularly useful in forecasting productivity for different machine types and operational settings, enabling more precise decision-making and resource allocation.

While there are limited examples of predictive machine learning models for production metrics in the forest industry, particularly for cut-to-length harvesters (Liski et al., 2020; Munis et al., 2022), future research should expand these capabilities across broader forest operations, incorporating whole-tree harvesting systems and diverse forestry conditions. By integrating machine learning, trend analysis, and predictive validation, future work should enhance the industry's ability to anticipate and respond to changing operational dynamics, ultimately improving efficiency, cost-effectiveness, and sustainability in timber harvesting operations.

## 7.5 Closing Statement

The findings of this research highlight the transformative potential of automated data collection and analysis in WT harvesting operations. By integrating OBC data with forest inventory information and conducting in-field productivity studies supported by advanced performance monitoring technology and statistical analytics, this study provides a comprehensive framework for automatically collecting and analyzing productivity data for WT felling machines. These advancements enable standardized, automated, and scalable productivity assessments across diverse harvesting conditions, addressing the existing knowledge gap in local productivity rates. In doing so, this research not only enhances operational efficiency but also lays the foundation for data-driven decision-making in the forestry sector.

As the industry moves toward greater digitalization and connectivity, the ability to collect and analyze machine performance data in real time will be critical for optimizing harvesting strategies, benchmarking productivity, and ensuring sustainable resource management. This research provides a strong methodological framework for future advancements in automated forest operations analysis.

Ultimately, the author hopes that this work contributes to the broader adoption of machine connectivity solutions, encouraging further research and innovation in real-time productivity monitoring, predictive modeling, and intelligent forest operations management. By bridging the gap between research and practice, this study supports the continued evolution of efficient, data-informed harvesting strategies that align with the economic and environmental demands of modern forestry.

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# Appendix A: Detailed Machine Description

This appendix gives a detailed description of machines that are introduced in Chapter 1 in the literature review. The following machines are commonly used in fully mechanized WT harvesting operations BC.

## A.1 Feller bunchers and feller directors

Feller bunchers cut, lift, and pile trees into bunches close to the stump. The number of trees they can bundle within one work cycle depends on the felling-head size and tree diameter. Feller directors are less suitable for bunching as their main task is to fell single trees. Carriers for both types of machines are categorized as either swing-to-tree or drive-to-tree machines and can vary greatly in their configuration (MacDonald 1999). Swing-to-tree feller bunchers are boom-mounted, usually excavator-based machines that travel on tracks. Drive-to-tree feller bunchers are typically rubber tire machines with the felling head directly mounted to the carrier. These two categories of carriers differ, especially in their reach. Swing-to-tree machines have a longer reach and are better suited for selection cuts and thinning operations. They are less dependent on favorable ground, as they do not need direct access to targeted trees. In addition, tracked machines are more suitable for working on wet and loose soils than rubber tire machines (Castro et al. 2016). Drive-to-tree machines depend on ground access to the trees to be harvested. Their optimal operation condition is on plain obstacle-free terrain with soils that offer sufficient traction, as they need adequate space to maneuver.

Felling heads for feller bunchers can be categorized into different groups. The most common are: (i) circular saw felling heads, also known as “hot saw” or “disc saw,” (ii) bar saw felling heads, and (iii) shear felling heads (Kellogg and Brink, 1992). Shearing heads are primarily used in forest stands with lower quality logs, as they can cause substantial butt damage while cutting the tree (MacDonald, 1999). Circular heads with a continuous rotating saw require a shorter felling time in their work cycle, as they cut through the tree faster than bar saw heads. Therefore, they can be more productive in suitable conditions. Bar saw heads, on the other hand, require less maintenance and lower investment cost and can be used in a broader range of tree diameters (Adebayo et al., 2007). Felling heads with the ability to grab, cut, and bunch several trees in one work cycle can increase the productivity up to 20 - 35% compared to single-grab felling heads (Castro et al. 2016). Feller directors are usually equipped with a directional bar saw felling head.

As these heads typically do not support the full weight of the tree, they can handle larger trees than feller bunchers (Richardson, 1989; MacDonald, 1999). Feller directors are typically used in winch-assist operation as they offer several advantages over feller bunchers, such as a lower risk of accidentally cutting the cable (Dyson and Boswell, 2016). Feller bunchers can also be implemented in an alternative CTL method, in which processors or single grip harvesters process the felled trees into the desired sorts at the stump. Forwarders extract these sorts for loading at the roadside (Hillman, 2004; Acuna and Kellogg, 2009).

## A.2 Skidders

One of the most common ground-based machines for primary transportation in timber harvesting operations are skidders (Uusitalo 2010; Castro et al. 2016). These machines are forest tractors specially designed to drag the felled logs to the desired place by lifting one end of the ground. Skidders are typically implemented in either fully- or semi-mechanized tree-length or WT harvesting operations. They can be categorized by their tractive system (tracked or wheeled) and their design to hold and drag the logs (e.g., cable, grapple). Skidders equipped with rubber tires can travel at comparably high speeds. Typical models have either four, six, or eight wheels. They require favorable terrain conditions and work the most efficiently on obstacle-free and flat ground. Due to their travel speed, they are suited for longer skidding distances while extracting higher payloads than tracked machines. Compared to wheeled machines, tracked skidders move slower. However, they offer higher stability and a higher tractive force.

Cable skidders are equipped with a winch and a cable that enables the operator to pull the logs to the machine. This type of skidder is suited for difficult terrain that does not allow the machine to travel to the logs and/or in operations where the logs are scattered. Grapple skidders are most suited to work with feller bunchers as their grapple allows them to lift pre-bunched logs. The advantage of extracting multiple logs in one bunch makes these machines more productive than cable skidders. Three types of grapples can be distinguished: (i) sorting grapples are designed to pick up individual or small numbers of large diameter logs, (ii) bunching grapples pick up large numbers of small-diameter logs, and (iii) hybrid grapples, which suit both scenarios of number and size of logs. The grapple is typically mounted to an arch on the back of the skidder. Three different types of arches exist on grapple skidders: (i) a single arch has a single set of cylinders that allows upward and downward movement. The range is limited to only vertical motions. This arch type is used in operations with short working cycles and large diameter logs. (ii) A second set of cylinders and a second pivot point allow vertical and horizontal movements of a dual arch. This increases the machine's effective reach and enables getting the load closer to the skidder, which increases its stability and traction. (iii) Swing boom grapples offer the greatest flexibility. The grapple arm can be moved to the rear and the side. The improved reach allows for shorter work cycles as the machine requires less maneuvering to grab the bundles or individual logs. The only drawback is that the gripper arm can only carry smaller loads. Skidders of this type can be used in more challenging terrain where the machine cannot necessarily reach the bundle (e.g., on soft ground or in selective harvesting and thinning operations) (MacDonald 1999).

The flexibility in use is the main advantage of cable skidders besides the low investment costs. The most significant disadvantage of these skidders is that they require the operator to leave the cabin and hook each load individually. The time spent choking and de-choking the loads increases the time per work cycle intensively (Castro et al. 2016). The advantages of grapple skidders over cable skidders are higher productivity due to shorter cycle times and increased operator safety. The operator does not have to leave the cabin to choke or de-choke the load (Längin et al. 2010).

Another variation of skidders is the clambunk skidder, a large, slow-moving, highly productive machine that can transport high payloads of logs. The logs are placed into the upward-facing grapple at the back of the machine with a rear-mounted log loader. Typically, several bunches are loaded during one cycle while the machine travels toward the landing. Since these machines are restricted to straight trails because of their large turning radius, clambunks are less likely to overturn and can work on slopes up to 60% (MacDonald 1999).

## A.3 Loader-Forwarder

Loader-forwarders are excavator-based loaders that move logs from the stump to the roadside or landing with a grapple attached to a boom. Also known as "hoe-chuckers" or "shovel-loggers," these machines handle each log several times before it reaches the roadside (four to five passes is considered normal). The distance per pass can reach up to 30–35 m for large machines. To reduce the number of passes and the travel distance of the loader-forwarders, the machines work either parallel or perpendicular to the road with backline distances up to 150 m (MacDonald 1999). Similar to other tracked machines, loader-forwarders can operate on slopes up to 35%. However, they can reach and pick logs out of sensitive zones with their boom, such as riparian areas or short steep pitches (Längin et al. 2010). Therefore, loader-forwarders are often used in combination with other equipment for primary transportation to increase the overall productivity of the entire system and make operations more economical. The economic advantage of this method is that it only requires one operator. Drawbacks are the short backline distances and the risk of sliding on thin soils on top of bedrock and snow (MacDonald 1999).

## A.4 Cable Yarders

When the terrain is inaccessible for ground-based machines or when the soil is of low carrying capacity, cable yarders are typically used for primary transport (Castro et al. 2016). The yarder is usually located at a landing or at the roadside to where it drags the felled logs by using two or more cables. The cable's deflection, the cable's clearance above the ground, the ground profile, and the size and power of the machines determine the payload a yarder can transport. Sufficient clearance and deflection allow the logs to be either partially or fully suspended of the ground. Full suspension reduces the disturbance of the soil to a minimum. However, the requirements on the vertical space between the ground and the carriage are higher, and the logs are constrained in length. In partial suspension, only the ends of the logs are lifted off the ground. Thereby the requirements on the strength of the yarding machine, cable design, and anchor support are lower (MacDonald 1999). In both types of suspension, an insufficient deflection and clearance might decrease the yarding distance below the machine's capacity, payload, and productivity. Proper engineering and layout of the cutblock for yarding are needed in order to keep the most suitable yarding system efficient and profitable. The different types of yarders can be classified based on four primary characteristics: configuration, mobility/carrier, the way the logs are held, and the size of the machine (MacDonald 1999). The main two configuration types that can be distinguished are high-lead/running-skyline and skyline systems. A high-lead yarding system consists of an inhaul, an outhaul drum, and two cables called haulback and mainline and is thereby the simplest multi-drum system. However, many yarders are equipped with a third utility drum. Skyline systems use a skyline that supplies lift for blocks, rigging, a carriage, and logs (WorkSafeBC 2006). If the carriage of this system runs on a haulback cable (as in grapple yarders), it is called a running skyline. A live skyline is a variation in which the skyline can be lowered or raised during the yarding. A standing skyline is a skyline fixed in position during yarding. The running-skyline system is a variation of the high-lead system in which the mainline and haulback line are connected through a rider or scab block to provide extra lift (MacDonald 1999; WorkSafeBC 2006).

Two types of yarders can be differentiated in terms of mobility. Swing yarders are rotating superstructures on either tracked or rubber tire carriers equipped with booms that face the cutblock and swing sideways in both directions. Tower yarders are stationary vertical spar trees that do not move their location during the yarding phase. Commonly, the methods used to hold the logs are either chokers or grapples. Chokers are metal ropes that wrap around the logs and close by the force of the logs' own weight. Grapples are large metal tongs that typically grab single logs. Cable yarding machines can vary greatly in their size. Due to the labor and equipment required, cable systems are often more expensive to own and operate than ground-based systems (MacDonald 1999).

## A.5 Processors

Machines used for mechanized processing can vary in design and function. Their purpose is to produce an intermediate product for a processing facility such as a saw or paper mill. Several groups of these machines can be distinguished. The type of processing machine used at the felling site strongly depends on the local industry, as they produce different products (MacDonald 1999). Chainflail delimber/debarker produce debarked untopped logs. They are often used in on-site chipping operations where either disc or drum chippers turn raw material into chips. Slashers are used to cut bunches of long logs into short logs at the operation site. They are used in operations that harvest smaller diameter trees. All of these machines can be either stationary or mobile. More common in sawlog production are dangle-head processors and stroke-delimbers.

Dangle-head processors delimb and buck felled stems into logs. Feeders push the stem through the head against delimbing knives, and a bar-saw cuts it into the desired log length. Similar to harvester heads, processor heads are attached to a boom mounted to an appropriate carrier. There are only a few differences in the design of the two types of heads, and these are mainly defined by their use. Sensors implemented in the heads measure the diameter and length of the stem that is being pushed through. It becomes easy to determine volume production and the machine's productivity with the collected information. Collecting size data of the stem can further allow optimization software to assist the operator with bucking decisions.

Stroke delimbers pick up, delimb and buck trees into the desired log assortments with a configuration of several grapples and a boom. A grapple fixed to the boom holds the butt end of the tree. When the boom slides back, it drags the stem along the delimbing knives of a second grapple. Logs are then piled, ready for secondary transportation. The range of applications for dangle-head processors is broader, however, both machines are typically used in WT harvesting operations (MacDonald 1999; Längin et al. 2010).

# Appendix B: Time Study Work Element Description

This appendix reports the definitions of work elements used for direct timing of the monitored machines. In the case of overlapping of different work elements, the element with highest priority (lower priority value) was recorded.

The work elements for feller bunchers were defined as:

- **Felling:** cutting of one or more trees. It includes complete cut (felling) of one or more trees or, in case of large diameter trees, partial cuts (partial felling). It starts when the machine is in position to cut a tree and stops when tree is partially or completely cut. Priority 1.
- **Bunching:** unloading and positioning of felled trees into bunches. In case of large trees this might only be guiding the tree into a certain felling direction and later repositioning into a bunch. It can also include subsequent tree repositioning onto a bunch. It starts at the end of felling or when the machine is in position to pick up a tree or adjust a deck and stops when the grab arms are fully open, and the trees are released. Priority 1.
- **Clearing:** removal of unmerchantable trees or snags or repositioning of any debris, logs, stumps or other obstacles to clear or built a path. It starts when the machine needs to stop its operation to fell non-merchantable trees or clear or create a path and stops once it continuous to work on primary task or moving. Priority 2.
- **Moving:** machine repositions and relocation within the block. It starts when at least one of the tracks starts moving and stops when both tracks stop moving. Priority 3.

The work elements for grapple skidders were defined as:

- **Travel empty:** unloaded machine relocation within the block, mainly to reach the pick-up location of a load. It starts when the unloaded machine begins to move its wheels and stops when machine has reached a bunch to be loaded. Priority 2.
- **Loading:** loading of bunches or individual stems into the grapple, including repositioning and reloading for better grip. It starts when the machine is in position to load and lowers and/or opens its grapple to pick up a load and stops when the loaded grapple is raised and/or closed for travel. Priority 1.

- **Travel loaded:** actual skidding of the trees, with the machine travelling loaded with bunches or individual stems from the pick-up location to the landing or other drop-off location. It starts when the machine begins to move its wheels after it has picked up a load and stops when the machine reaches the landing or other drop-off location. Priority 2.
- **Unloading:** unload of individual stems or bunches at the landing. This includes seldom piling of bunches onto deck. It starts when the machine reaches the landing and starts to lower and/or open its grapple and stops when the load has been dropped off and the machine leaves the drop off location. Priority 1.

The work elements for log loaders shared the definition of moving and clearing, while their primary 'handling wood' work task was differentiated between loader-forwarders, decking machine, and truck loader. Work elements for log loaders used as loader-forwarders were defined as:

- **Loading-forwarding:** progressive movement of trees from felling area to roadside by means of consecutive shoveling. It includes swing empty, grab trees, swing loaded, drop off into bunch or deck. It might include further piling and decking of moved trees. It starts when the machine is in position to pick up a tree within reach and stops when the machine has released the tree into a bunch or deck. Priority 1.
- **Clearing:** repositioning of any debris, logs, stumps or other obstacles to clear or built a path. It starts when the machine needs to stop its operation to clear or create a path and stops once it continuous to work on primary task or moving. Priority 2.
- **Moving:** see definition of 'moving' in the feller buncher section. Priority 3.

Work elements for log loaders used as decking machine were defined as:

- **Decking:** movement of trees onto a deck or relocation of trees within a deck, normally following the unloading phase of a skidder. It includes swing empty, grab trees, swing loaded, drop off into a deck. It starts when the machine is in position to pick up a tree within reach and stops when the machine has released the tree into a deck. Priority 1.
- **Clearing:** see definition of 'clearing' in the loader-forwarder section. Priority 2.
- **Moving:** see definition of 'moving' in the feller buncher section. Priority 3.

Work elements for log loaders used as truck loader were defined as:

- **Loading:** movement of logs from a deck onto the trailer of a logging truck or relocation of logs on the deck during the loading process. It includes swing empty, grab trees, swing loaded, drop off into the trailer of a logging truck or a deck. It starts when the machine is in position to pick up a log within reach and stops when the machine has released the logs into the trailer. Priority 1.
- **Decking:** relocation of logs within a deck or on a different deck when a logging truck is not available for loading. It includes swing empty, grab trees, swing loaded, drop off into a deck. It starts when the machine is in position to pick up a tree within reach and stops when the machine has released the tree into a deck. Priority 1.
- **Clearing:** see definition of 'clearing' in the loader-forwarder section. Priority 2.
- **Moving:** see definition of 'moving' in the feller buncher section. Priority 3.

The work elements for the dangle head processor were defined as follow. Note that a loading phase is included in the work element description because the processor was also used for loading trucks (for this reason this type of machine is frequently referred to as 'proader'):

- **Processing:** processing of trees, including picking up from a deck or from the landing of a cable yarder, handling, delimbing, crosscutting and stacking logs. It starts when the machine is in position to pick up a tree and stops when the machine has piled the logs onto a deck or when the machine starts a different element. Priority 1.
- **Decking:** see definition of 'decking' in the truck loader section. Priority 2.
- **Loading:** see definition of 'loading' in the truck loader section. Priority 2.
- **Clearing:** see definition of 'clearing' in the loader-forwarder section. Priority 3.
- **Moving:** see definition of 'moving' in the feller-buncher section. Priority 4.

# Appendix C: Modeling Workflow and Supplementary Results of Chapter 6

The following Appendix provides a step-by-step modeling workflow used for the analyses in Chapter 6, including additional diagnostic plots and model comparisons not presented in the main text. It is intended as a practical guide for replication or adaptation of productivity modeling with large-scale, long-term production data. All relevant R code and supplementary outputs are included to enhance transparency and reproducibility of the methods

## C.1 Dataset

Production reports (observation points): 3081 (Company A: 1565; Company B: 1516)

Machines: 71 (Company A: 29; Company B: 42)

Dependent variable: Productivity in $m^3/PMH_{15}$ (Prod)

Descriptive variables: average stem size in $m^3$/tree (AvgStemSiz), average volume per hectare in $m^3$/ha (VolumePerH), average stem density in n/ha (AvgStemDen), average ground slope in % (AvgSlopePer)

Random factors: BlockId, MachineId

| Date | Company | BlockId | MachineId | Prod | AvgStemSiz | AvgStemDen | AvgSlopePer |
|---|---|---|---|---|---|---|---|
| 2022-02-01 | A | BLA0050 | 77 | 50.99 | 0.52 | 602 | 27.0980506 |
| 2022-02-09 | A | BLA0050 | 77 | 44.88 | 0.53 | 602 | 29.9116389 |
| 2022-02-10 | A | BLA0050 | 77 | 47.09 | 0.51 | 602 | 34.9155757 |
| 2022-02-11 | A | BLA0050 | 77 | 32.03 | 0.51 | 602 | 42.0764426 |
| 2022-02-14 | A | BLA0050 | 77 | 37.64 | 0.54 | 602 | 38.6690516 |
| 2022-02-15 | A | BLA0050 | 77 | 40.62 | 0.5 | 602 | 35.217035 |
| 2022-02-16 | A | BLA0050 | 77 | 38.57 | 0.53 | 602 | 38.5475232 |
| 2022-06-24 | B | HAT104 | 32 | 93.31 | 0.45 | 656 | 3.93776527 |
| 2022-06-27 | B | HAT104 | 83 | 57.02 | 0.43 | 656 | 6.83234007 |
| 2022-06-27 | B | HAT104 | 33 | 67.69 | 0.43 | 656 | 5.74211845 |
| 2022-06-27 | B | HAT104 | 32 | 80.56 | 0.45 | 656 | 6.03063716 |
| 2022-06-28 | B | HAT104 | 83 | 50.56 | 0.45 | 656 | 3.48374433 |
| 2022-06-28 | B | HAT104 | 33 | 61.81 | 0.45 | 656 | 5.47386169 |
| 2022-06-28 | B | HAT104 | 32 | 61.66 | 0.45 | 656 | 6.00618922 |

*Figure C.1 Example of dataset structure.*

## C.2 Daily Machine-Level Analysis

### C.2.1 Descriptive Statistics

```
# Get mean, sd, iqr, median
sapply(data[, c("Prod", "AvgStemSiz", "VolumePerH", "AvgStemDen",
                "AvgGroundS")],
  function(x) {c(
    Mean   = mean(x, na.rm = TRUE),
    SD     = sd(x, na.rm = TRUE),
    IQR    = IQR(x, na.rm = TRUE),
    Median = median(x, na.rm = TRUE))})
           Prod AvgStemSiz VolumePerH AvgStemDen AvgGroundS
Mean   53.95461  0.3970432   351.7273  1066.6118   18.17412
SD     26.07627  0.2363645   161.2873   633.6649   10.03915
IQR    34.87000  0.2300000   259.0000   881.1400   13.91000
Median 49.52000  0.3100000   329.7300   788.2200   15.83000

# Histogram
ggplot(data, aes(x = Prod)) +
  geom_histogram(binwidth = 1, fill = "blue", alpha = 0.7) +
  labs(
    title = "Histogram of Productivity",
    x = expression("Productivity (m"^3*"/PMH"["15"]*")"),
    y = "Frequency (n)")
```

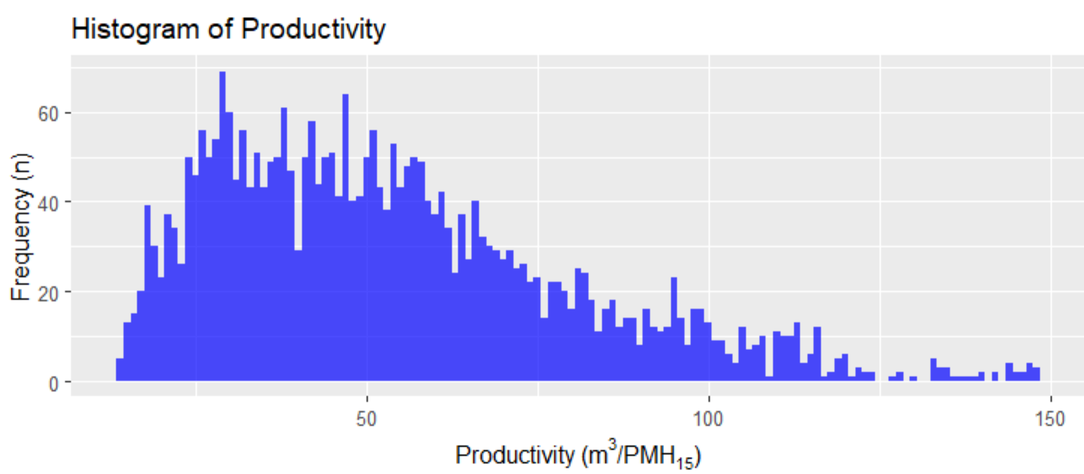


*Figure C.2 Histogram of daily machine-level productivity.*

```
# Stem Size
ggplot(data, aes(x = AvgStemSiz, y = Prod)) +
  geom_point(color = "black", alpha = 0.6, size = 0.8) +
  geom_smooth(method = "lm", color = "black", se = FALSE) +
  labs(
    title = "Productivity vs. Average Stem Size",
    x = expression("Average Stem Size (m"^3*"/tree)"),
    y = expression("Productivity (m"^3*"/PMH"["15"]*")")) +
  scale_y_continuous(limits = c(0, 150)) +
  theme_classic()
```


*Figure C.3 Scatterplot showing the relation between Productivity and Average Stem Size at daily machine-level observations. Plot includes linear regression line.*

```
# Volume per ha
ggplot(data, aes(x = VolumePerH, y = Prod)) +
  geom_point(color = "black", alpha = 0.6, size = 0.8) +
  geom_smooth(method = "lm", color = "black", se = FALSE) +
  labs(
    title = "Productivity vs. Volume per ha",
    x = expression("Volume per ha (m"^3*"/ha)"),
    y = expression("Productivity (m"^3*"/PMH"["15"]*")")
  ) +
  scale_y_continuous(limits = c(0, 150)) +
  theme_classic()
```

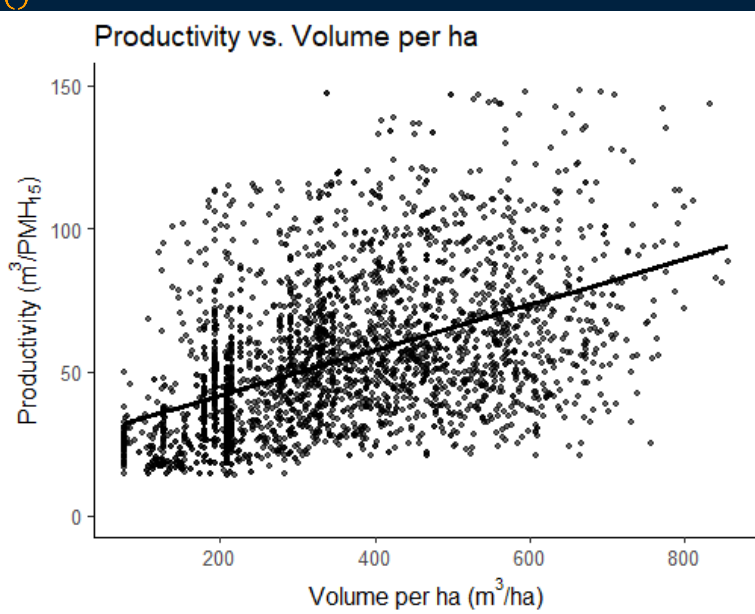


*Figure C.4 Scatterplot showing the relation between Productivity and Volume Per Hectare at daily machine-level observations. Plot includes linear regression line.*

```
# Stem Density
ggplot(data, aes(x = AvgStemDen, y = Prod)) +
  geom_point(color = "black", alpha = 0.6, size = 0.8) +
  geom_smooth(method = "lm", color = "black", se = FALSE) +
  labs(
    title = "Productivity vs. Average Stem Density",
    x = expression(paste("Average Stem Density (trees/", ha,")")),
    y = expression("Productivity (m"^3 * "/PMH"["15"] * ) +
  scale_y_continuous(limits = c(0, 150)) +
  theme_classic()
```

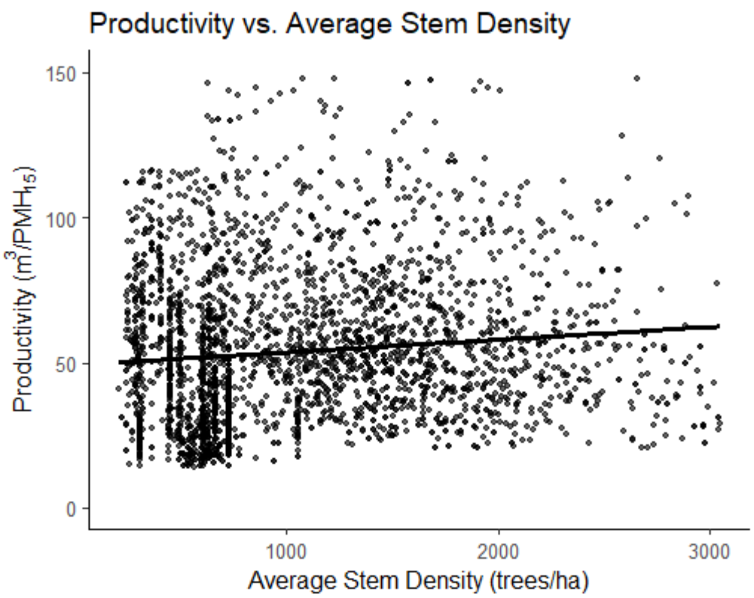


*Figure C.5 Scatterplot showing the relation between Productivity and Average Stem Density at daily machine-level observations. Plot includes linear regression line.*

```
# Ground slope
ggplot(data, aes(x = AvgGroundS, y = Prod)) +
  geom_point(color = "black", alpha = 0.6, size = 0.8) +
  geom_smooth(method = "lm", color = "black", se = FALSE) +
  labs(
    title = "Productivity vs. Average Ground Slope",
    x = expression(paste("Average Ground Slope (", "%", ")")),
    y = expression("Productivity (m"^3 * "/PMH"["15"] * ")")) +
  theme_classic()
```

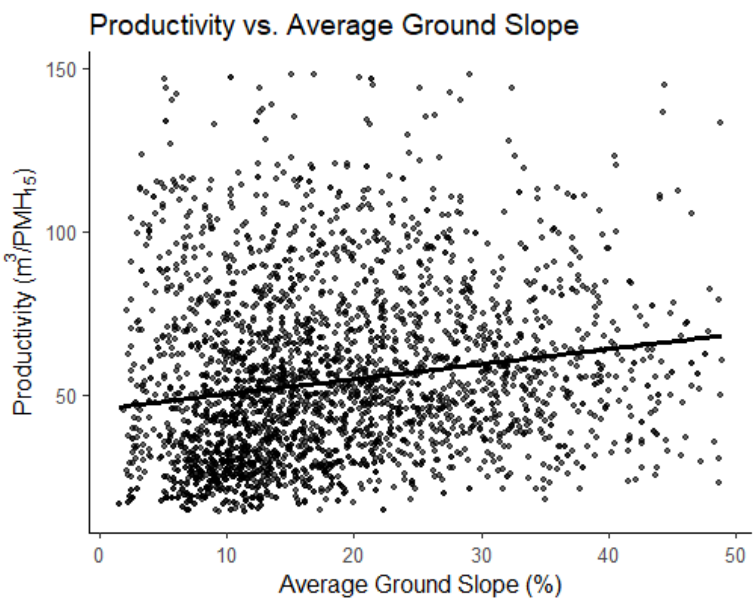


*Figure C.6 Scatterplot showing the relation between Productivity and Average Ground Slope at daily machine-level observations. Plot includes linear regression line.*

```
## Create spaghetti plots with linear regression ----
# Productivity vs AvgStemSiz with linear regression
ggplot(data, aes(x = AvgStemSiz, y = Prod, group = MachineId,
       color = as.factor(MachineId))) +
  geom_smooth(method = "lm", se = FALSE) + # Linear regression line
  labs(
    title = "Spaghetti Plot with Regression: Productivity vs AvgStemSiz",
    x = expression("Average Stem Size (m"^3*")"),
    y = expression("Productivity (m"^3*"/PMH"["15"]*")")) +
  theme_minimal() +
  theme(legend.position = "none")
```

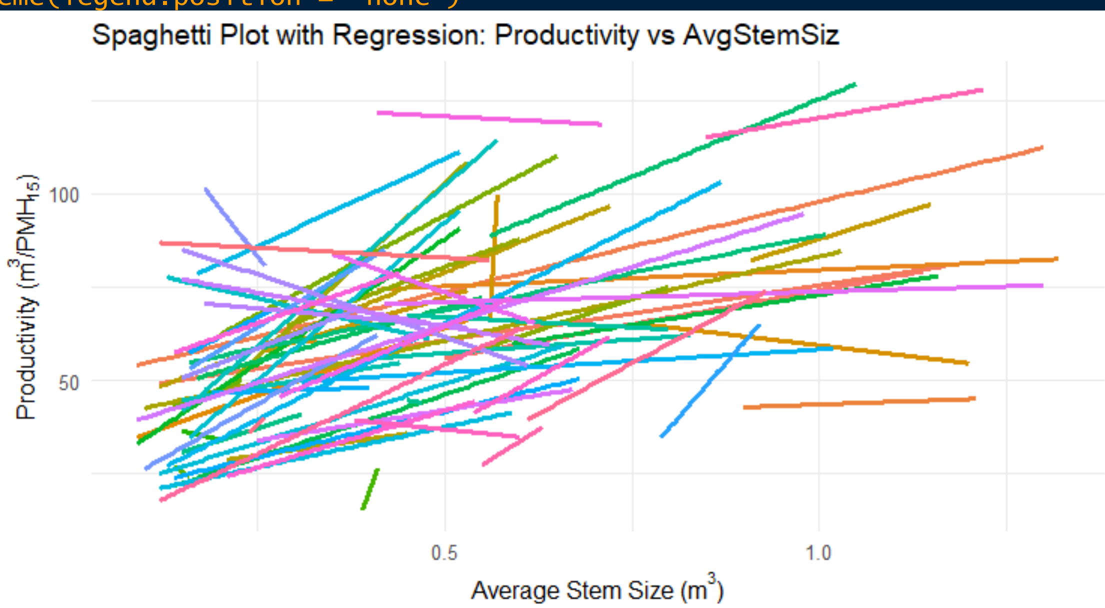


*Figure C.7 Spaghetti plot showing the regression between Productivity and Average Stem Size for every machine.*

```r
# Productivity vs Volume per ha with linear regression
ggplot(data, aes(x = VolumePerH, y = Prod, group = MachineId,
       color = as.factor(MachineId))) +
  geom_smooth(method = "lm", se = FALSE) + # Linear regression line
  labs(
    title = "Spaghetti Plot with Regression: Productivity vs Volume per ha",
    x = expression("Volume per ha (m"^3*"/ha)"),
    y = expression("Productivity (m"^3*"/PMH"["15"]*")")) +
  theme_minimal() +
  theme(legend.position = "none")
```

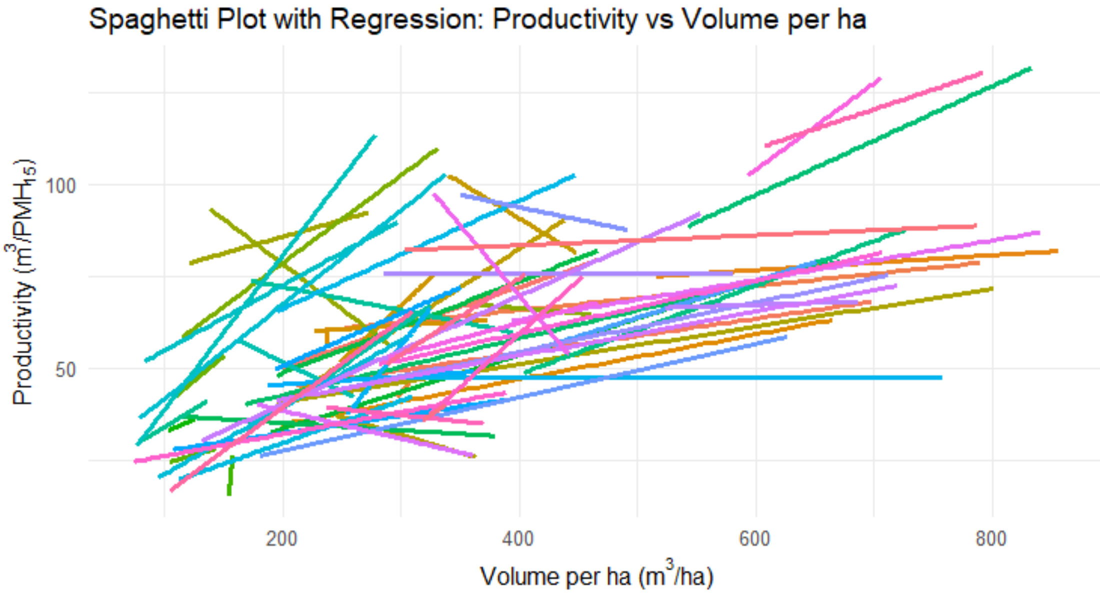


*Figure C.8 Spaghetti plot showing the regression between Productivity and Volume Per Hectare for every machine.*

```r
# Productivity vs AvgStemDen with linear regression
ggplot(data, aes(x = AvgStemDen, y = Prod, group = MachineId,
       color = as.factor(MachineId))) +
  geom_smooth(method = "lm", se = FALSE) + # Linear regression line
  labs(
    title = "Spaghetti Plot with Regression: Productivity vs AvgStemDen",
    x = "Average Stem Density (trees/ha)",
    y = expression("Productivity (m"^3*"/PMH"["15"]*")")) +
  theme_minimal() +
  theme(legend.position = "none")
```

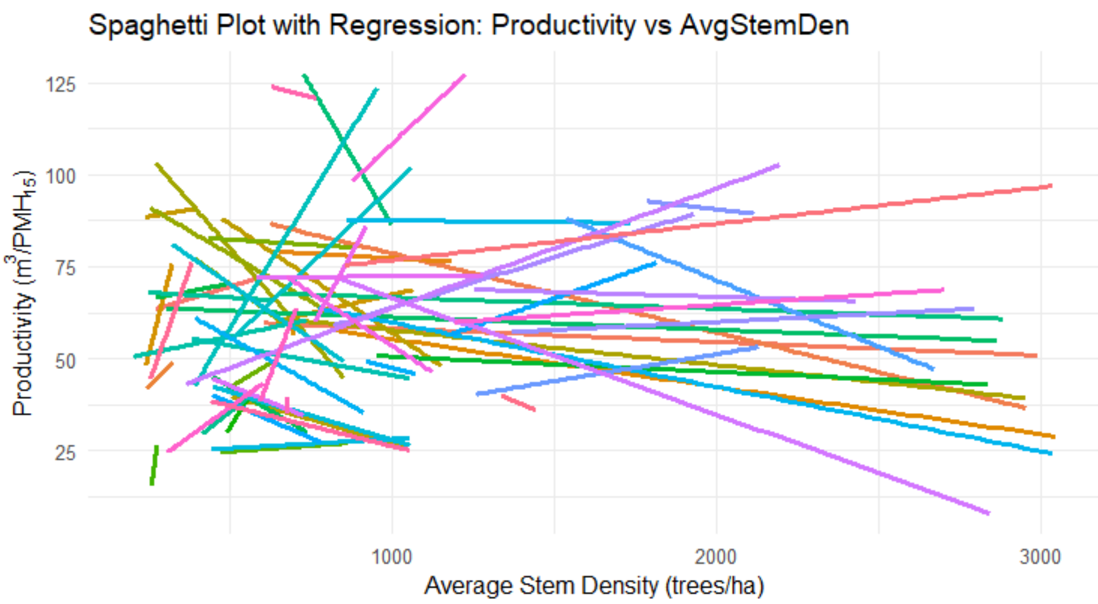


*Figure C.9 Spaghetti plot showing the regression between Productivity and Average Stem Density for every machine.*

```
# Productivity vs AvgSlopePer with linear regression
ggplot(data, aes(x = AvgGroundS, y = Prod, group = MachineId,
       color = as.factor(MachineId))) +
  geom_smooth(method = "lm", se = FALSE) + # Linear regression line
  labs(
    title = "Spaghetti Plot with Regression: Productivity vs AvgGroundS",
    x = "Average Slope (%)",
    y = expression("Productivity (m"^3*"/PMH"["15"]*")")) +
  theme_minimal() +
  theme(legend.position = "none")
```

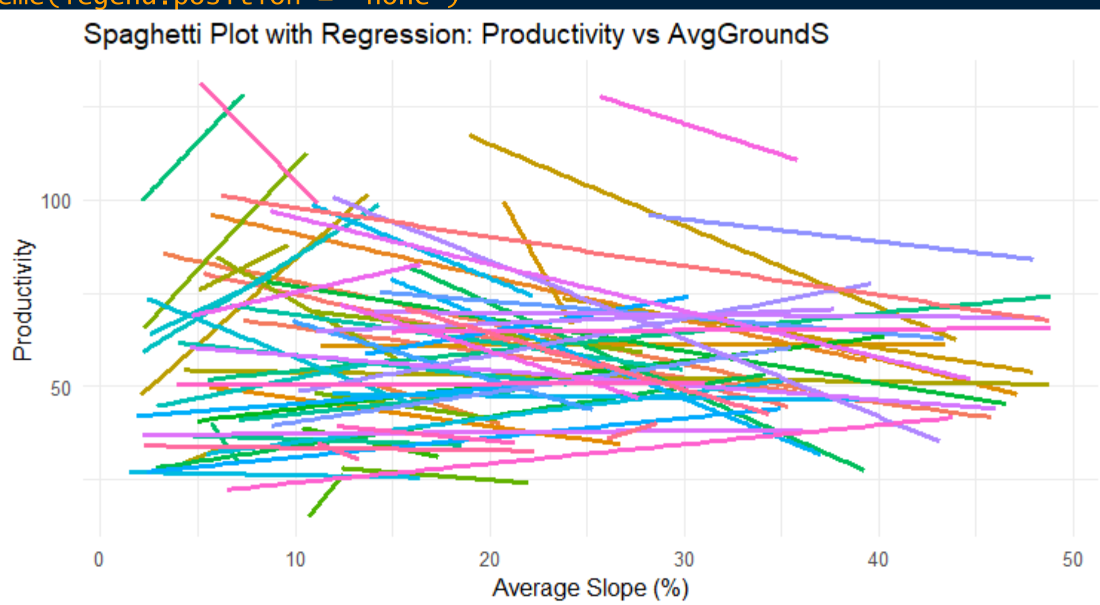


*Figure C.10 Spaghetti plot showing the regression between Productivity and Average Ground Slope for every machine.*

### C.2.2 nlme Homoscedastic Model

```
## Fit homoscedastic model with nested random effects with lme ----
mod_homoscedastic <- lme(
  fixed   = Prod ~ 0 + AvgStemSiz + VolumePerH + AvgStemDen + AvgGroundS,
  random  = ~ 1 | BlockId/MachineId,  # keep random intercepts the same
  data    = data,
  control = lmeControl(optimMethod = "BFGS"))
# Print the summary of the model
summary(mod_homoscedastic)
Linear mixed-effects model fit by REML
  Data: data
       AIC      BIC    logLik
  26694.12 26736.34 -13340.06

Random effects:
 Formula: ~1 | BlockId
        (Intercept)
StdDev:    20.99262

 Formula: ~1 | MachineId %in% BlockId
        (Intercept) Residual
StdDev:    10.43618 16.27567

Fixed effects:  Prod ~ 0 + AvgStemSiz + VolumePerH + AvgStemDen + AvgGroundS
              Value Std.Error   DF   t-value p-value
AvgStemSiz 60.05265  4.305313 2760 13.948498       0
VolumePerH  0.07023  0.006362 2760 11.038688       0
AvgStemDen  0.01115  0.001226 2760  9.099148       0
AvgGroundS -0.49693  0.056483 2760 -8.797885       0
 Correlation:
           AvgStS VlmPrH AvgStD
VolumePerH -0.772
AvgStemDen  0.364 -0.422
AvgGroundS -0.141 -0.206 -0.133

Standardized Within-Group Residuals:
        Min          Q1         Med          Q3         Max
-3.35698600 -0.51607217 -0.05229436  0.46237940  5.50942520

Number of Observations: 3081
Number of Groups:
               BlockId MachineId %in% BlockId
                   218                    318

# Confidence intervals
intervals_mod_homoscedastic <- intervals(mod_homoscedastic, which = "fixed")
intervals_mod_homoscedastic
Approximate 95% confidence intervals

 Fixed effects:
                  lower        est.       upper
AvgStemSiz 51.610690924 60.05265175 68.49461257
VolumePerH  0.057756799  0.07023230  0.08270780
AvgStemDen  0.008749995  0.01115353  0.01355706
AvgGroundS -0.607687606 -0.49693376 -0.38617991

# Compute R² values for mixed model Nakagawa, S., & Schielzeth, H. (2013)
r2_values <- r.squaredGLMM(mod_homoscedastic)
# Print R² values
print(r2_values)
           R2m       R2c
[1,] 0.3149303 0.7771971
```

```
## Extract residuals and fitted values
resid_homoscedastic <- residuals(mod_homoscedastic, type = "normalized")
fitted_homoscedastic <- fitted(mod_homoscedastic)

# Plot residuals vs. fitted values
plot(fitted_homoscedastic, resid_homoscedastic,
     xlab = "Fitted Values",
     ylab = "Residuals",
     main = "Homoscedastic Residuals vs Fitted Values")
abline(h = 0, col = "red")
```

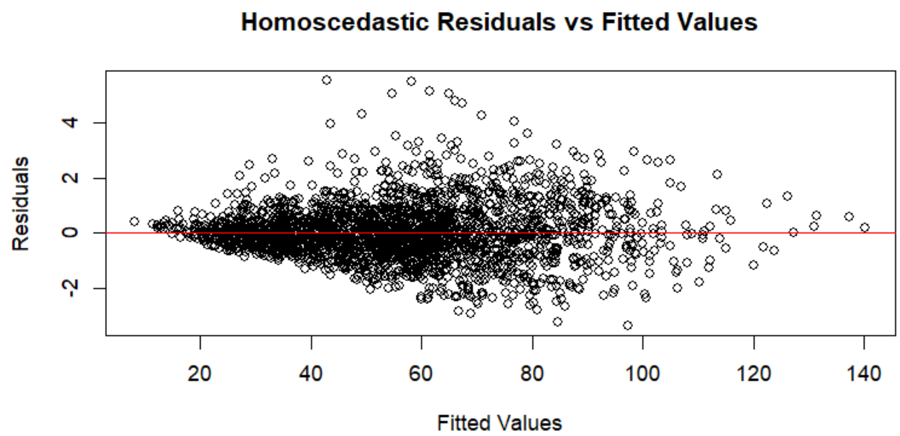


*Figure C.11 Residuals of the homoscedastic daily machine-level model plotted against the fitted values.*

```
Add residuals to the dataset
data$resid_homoscedastic <- resid_homoscedastic

# Define a list of covariates to explore
variables_to_plot <- c("AvgStemSiz", "VolumePerH", "AvgStemDen",
                       "AvgGroundS")

# Loop through each variable and create scatter plots
plots <- lapply(variables_to_plot, function(var) {
  ggplot(data, aes_string(x = var, y = "resid_homoscedastic")) +
    geom_point(alpha = 0.6) +
    geom_smooth(method = "loess", color = "blue", se = FALSE) +
    labs(title = paste("Residuals vs", var),
         x = var,
         y = "Residuals") +
    theme_minimal()})

# Display all plots
for (plot in plots) {
  print(plot)}
```

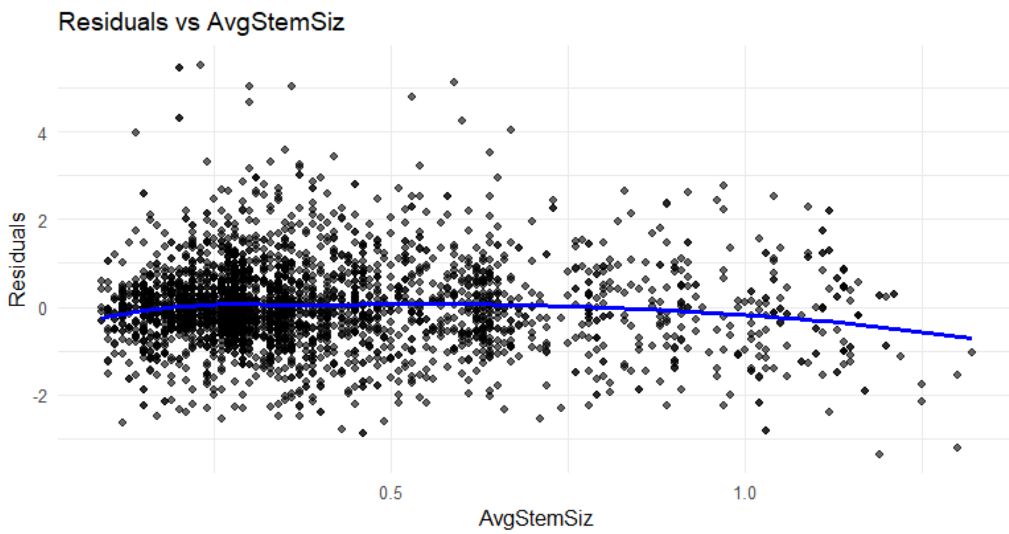


*Figure C.12 Residuals of the homoscedastic daily machine-level model plotted against Average Stem Size.*

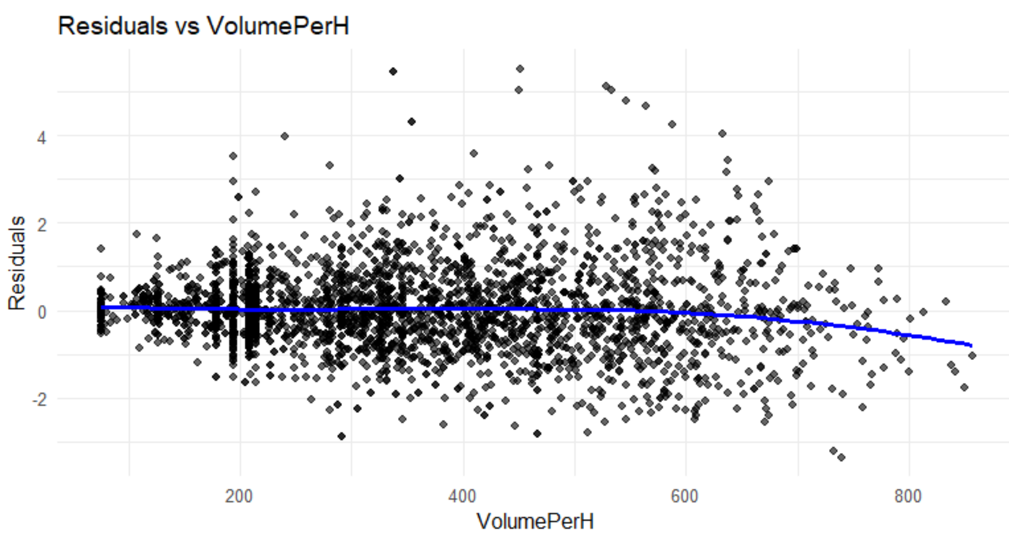


*Figure C.13 Residuals of the homoscedastic daily machine-level model plotted against Average Stem Size.*

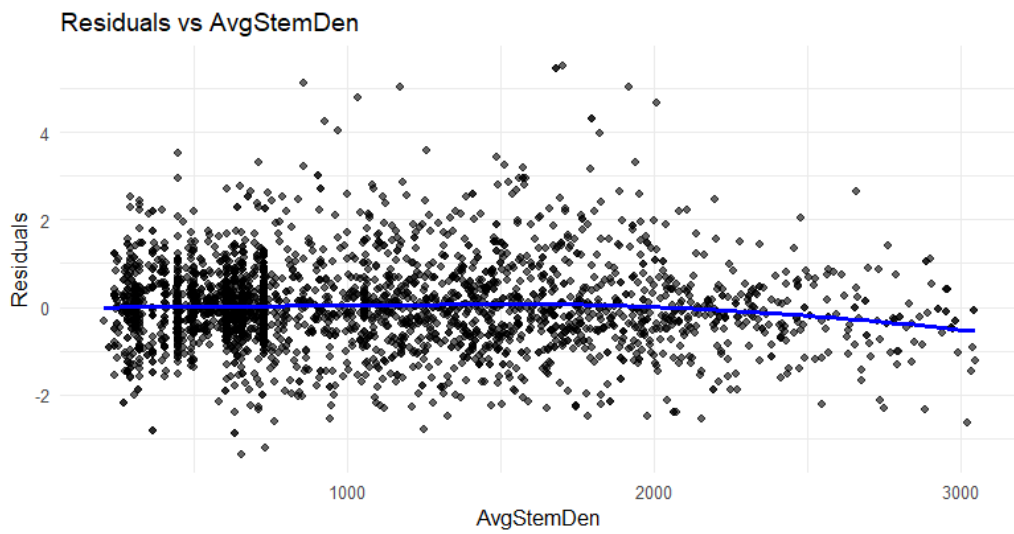


*Figure C.14 Residuals of the homoscedastic daily machine-level model plotted against Average Stem Density.*

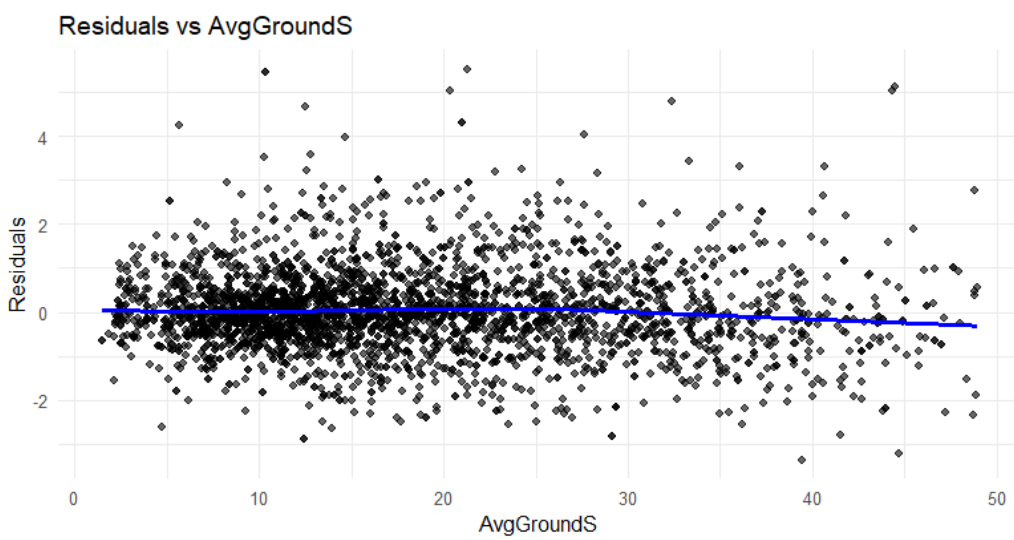


*Figure C.15 Residuals of the homoscedastic daily machine-level model plotted against Average Ground Slope.*

### C.2.3 nlme Heteroscedastic Model

```
## Fit heteroscedastic model with nlme 0 intercept ----
mod_heteroscedastic <- nlme::lme(
  fixed = Prod ~ 0 + AvgStemSiz + VolumePerH + AvgStemDen + AvgGroundS,
Fixed effects + Comapany if using "Both"
  random = ~ 1 | BlockId / MachineId,
  data = data,
  weights = nlme::varIdent(form = ~ 1 | MachineId),
  control = lmeControl(opt = "optim", maxIter = 10000000,
                       msMaxIter = 10000000, tolerance = 1e-4))
# Summary of the model
summary(mod_heteroscedastic)
Linear mixed-effects model fit by REML
  Data: data
       AIC      BIC    logLik
  25982.02 26446.46 -12914.01

Random effects:
 Formula: ~1 | BlockId
        (Intercept)
StdDev:    19.40551

Formula: ~1 | MachineId %in% BlockId
        (Intercept) Residual
StdDev:    9.935775  33.9087

Variance function:
 Structure: Different standard deviations per stratum
 Formula: ~1 | MachineId
 Parameter estimates:
        66         70        115        753        604         13
1.00000000 0.88172348 0.57386789 0.54344265 0.40914595 0.59035996
        14         15         12        675        616         17
0.44852092 0.51384878 0.64671465 0.45423952 0.54658038 0.39212271
       784        807        190         97         64        129
0.42877992 0.49617057 0.32704210 0.63107756 0.73191589 0.83709780
        61         63        799          6         90        114
0.37137763 0.66581724 0.42117751 0.42798132 0.48980688 0.47914423
       161         77       1350        164         54        693
0.51985633 0.15078013 0.47060730 0.25832844 0.24347284 0.34841541
       133       1401         32         35        241        245
0.41755323 0.95892374 0.27607880 0.51801640 0.37949304 0.29326586
       261        253       1423        586       1365        141
0.82801521 0.60094619 0.52380498 0.21675608 0.62397246 0.34127782
       400        194        658         33         83       1311
0.33033708 0.60326469 0.77725888 0.17577480 0.19154514 0.98441242
        82       1404       1286        195       1379        224
0.10191084 0.28174028 0.33142674 0.04859566 0.47486864 0.40435691
       233        237         18        723         49        756
0.51160716 0.31944268 0.20403535 0.53979210 0.29527672 0.46112201
      1386       1388        719         45       1361       1440
0.36300012 0.29783412 0.84431125 0.68965343 0.67943528 0.19377106
      1444       1447       1450         91       1449
0.46799366 0.11368220 0.14143934 0.08204023 0.20672182
Fixed effects:  Prod ~ 0 + AvgStemSiz + VolumePerH + AvgStemDen + AvgGroundS
              Value Std.Error   DF    t-value p-value
AvgStemSiz 67.99345  4.371209 2760  15.554837       0
VolumePerH  0.05943  0.006432 2760   9.239607       0
AvgStemDen  0.01236  0.001246 2760   9.918521       0
AvgGroundS -0.46146  0.044748 2760 -10.312530       0
 Correlation:
           AvgStS VlmPrH AvgStD
VolumePerH -0.801
AvgStemDen  0.372 -0.475
```

```
AvgGroundS -0.108 -0.161 -0.116

Standardized Within-Group Residuals:
       Min         Q1        Med         Q3        Max
-3.3068658 -0.5803406 -0.0655735  0.5767501  4.8911340

Number of Observations: 3081
Number of Groups:
               BlockId MachineId %in% BlockId
                   218                    318

# Confidence intervals
intervals_mod_heteroscedastic <- intervals((mod_heteroscedastic,
                                            which = "fixed")
intervals_mod_heteroscedastic
Approximate 95% confidence intervals

 Fixed effects:
                  lower        est.        upper
AvgStemSiz 59.422275573 67.99344675 76.56461793
VolumePerH  0.046816619  0.05942850  0.07204038
AvgStemDen  0.009914398  0.01235736  0.01480033
AvgGroundS -0.549206962 -0.46146419 -0.37372142

# Compute R² values for mixed model Nakagawa, S., & Schielzeth, H. (2013)
r2_values <- r.squaredGLMM(mod_heteroscedastic)
# Print R² values
print(r2_values)
           R2m       R2c
[1,] 0.1888008 0.4260534

## Extract residuals and fitted values
resid_heteroscedastic <- residuals(mod_heteroscedastic, type = "normalized")
fitted_heteroscedastic <- fitted(mod_heteroscedastic)

# Plot residuals vs. fitted values
plot(fitted_heteroscedastic, resid_heteroscedastic,
     xlab = "Fitted Values",
     ylab = "Residuals",
     main = "Heteroscedastic Residuals vs Fitted Values")
abline(h = 0, col = "red")
```

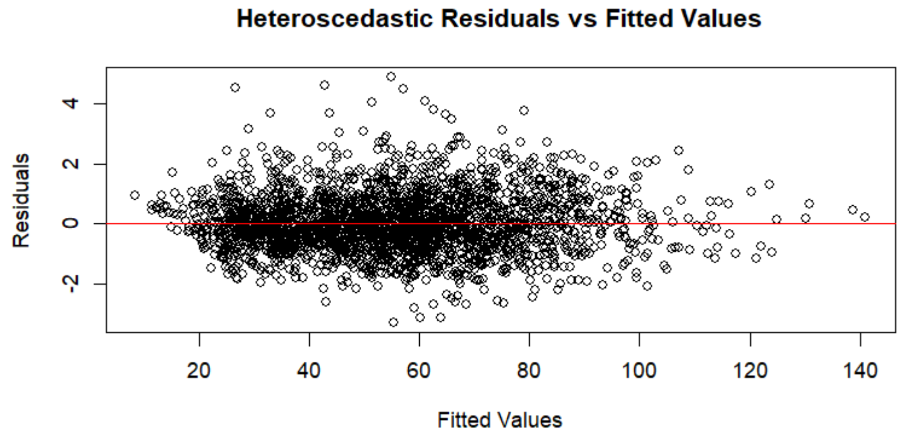


*Figure C.16 Residuals of the heteroscedastic daily machine-level model plotted against the fitted values.*

## C.2.4 nlme Heteroscedastic Model (reduced)

```
## Fit heteroscedastic model with nlme excluding machines with less than
observations ----
# Identify machines with few observations
machines_few_obs <- obs_by_machine_df$MachineId
                   [obs_by_machine_df$NumObservations < 10]

# Filter data to exclude machines with fewer than 10 observations
data_filtered <- subset(data, !(MachineId %in% machines_few_obs))

# Fit model
mod_filtered <- nlme::lme(
  Prod ~ AvgStemSiz + AvgStemDen + AvgGroundS + Company,
  random = ~ 1 | BlockId / MachineId,
  data = data_filtered,
  weights = nlme::varIdent(form = ~ 1 | MachineId),
  control = lmeControl(opt = "optim", maxIter = 10000000,
                       msMaxIter = 10000000, tolerance = 1e-4))

summary(mod_filtered)
Linear mixed-effects model fit by REML
  Data: data_filtered
       AIC      BIC    logLik
  24671.75 24964.86 -12286.88

Random effects:
 Formula: ~1 | BlockId
        (Intercept)
StdDev:    22.73094

 Formula: ~1 | MachineId %in% BlockId
        (Intercept) Residual
StdDev:    9.337431 34.24887

Variance function:
 Structure: Different standard deviations per stratum
 Formula: ~1 | MachineId
 Parameter estimates:
       66        70       115       604        13        14        15
1.0000000 0.8653578 0.5677398 0.4006189 0.5816058 0.4424556 0.5074042
       12       675        17        97        64       129        61
0.6408008 0.4492755 0.3834492 0.6230461 0.7280970 0.8225976 0.3686206
```

```
       63        90       114       161        77      1350       164
0.6589046 0.4851267 0.4740042 0.5151402 0.1492185 0.4637149 0.2557224
       54       693      1401        32       245       261       253
0.2409804 0.3448690 0.1539549 0.2732357 0.2550591 0.8003126 0.5526610
     1423      1365       400       194       658        33        83
0.4640026 0.6169596 0.3246434 0.5976658 0.7681370 0.1733555 0.1889716
     1379       224       233       237       723       756      1386
0.4695647 0.4005294 0.5067415 0.3156879 0.5343905 0.4535026 0.3576992
      719
0.8359146
Fixed effects:  Prod ~ 0 + AvgStemSiz + VolumePerH + AvgStemDen + AvgGroundS
              Value Std.Error   DF   t-value p-value
AvgStemSiz 68.68587  4.768340 2657 14.404567       0
VolumePerH  0.05673  0.006784 2657  8.362839       0
AvgStemDen  0.01115  0.001313 2657  8.495876       0
AvgGroundS -0.46210  0.046614 2657 -9.913373       0
 Correlation: 
           AvgStS VlmPrH AvgStD
VolumePerH -0.792              
AvgStemDen  0.373 -0.429       
AvgGroundS -0.097 -0.167 -0.102

Standardized Within-Group Residuals:
        Min          Q1         Med          Q3         Max 
-3.30353149 -0.57153712 -0.07003705  0.56939135  4.89030608 

Number of Observations: 2931
Number of Groups: 
               BlockId MachineId %in% BlockId 
                   184                    271 

# Confidence intervals
intervals_mod_filtered <- intervals(mod_filtered, which = "fixed")
intervals_mod_filtered
Approximate 95% confidence intervals

Fixed effects:
                  lower        est.      upper
AvgStemSiz 59.335834929 68.68586803 78.0359011
VolumePerH  0.043430948  0.05673337  0.0700358
AvgStemDen  0.008577546  0.01115127  0.0137250
AvgGroundS -0.553503371 -0.46210030 -0.3706972

# Compute R² values for mixed model Nakagawa, S., & Schielzeth, H. (2013)
r2_values <- r.squaredGLMM(mod_filtered)
# Print R² values
print(r2_values)
           R2m       R2c
[1,] 0.1624396 0.4470914

## Extract residuals and fitted values
resid_filtered <- residuals(mod_filtered, type = "normalized")
fitted_filtered <- fitted(mod_filtered)

# Plot residuals vs. fitted values
plot(fitted_filtered, resid_filtered,
     xlab = "Fitted Values",
     ylab = "Residuals",
     main = "Heteroscedastic red. Residuals vs Fitted Values")
abline(h = 0, col = "red")
```

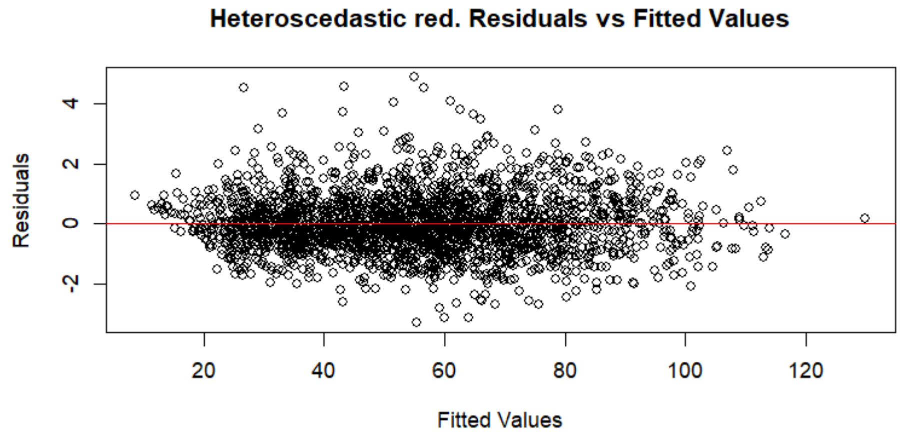


*Figure C.17 Residuals of the reduced heteroscedastic daily machine-level model plotted against the fitted values.*

## C.3 Cutblock-Level Analysis

### C.3.1 Descriptive Statistics

```
# Get mean, sd, iqr, median in one go for each numeric column
sapply(data[, c("Prod", "AvgStemSiz", "VolumePerH", "AvgStemDen", "AvgGroundS
", "BlockSiz")],
       function(x) {
  c(
    Mean   = mean(x, na.rm = TRUE),
    SD     = sd(x, na.rm = TRUE),
    IQR    = IQR(x, na.rm = TRUE),
    Median = median(x, na.rm = TRUE)
  )})
           Prod AvgStemSiz VolumePerH AvgStemDen AvgGroundS BlockSiz
Mean   70.85903  0.4739248   357.4339   894.1355   17.28272 18.03196
SD     23.44880  0.2476310   155.4571   538.2786   10.47102 16.59755
IQR    36.16843  0.3061894   209.2892   658.0791   17.36379 18.31300
Median 69.41825  0.4017309   337.0563   706.0231   15.31867 12.95700

# Histogram
ggplot(data, aes(x = Prod)) +
  geom_histogram(binwidth = 1, fill = "blue", alpha = 0.7) +
  labs(
    title = "Histogram of Productivity",
    x = expression("Productivity (m"^3*"/PMH"["15"]*")"),
    y = "Frequency (n)")
```

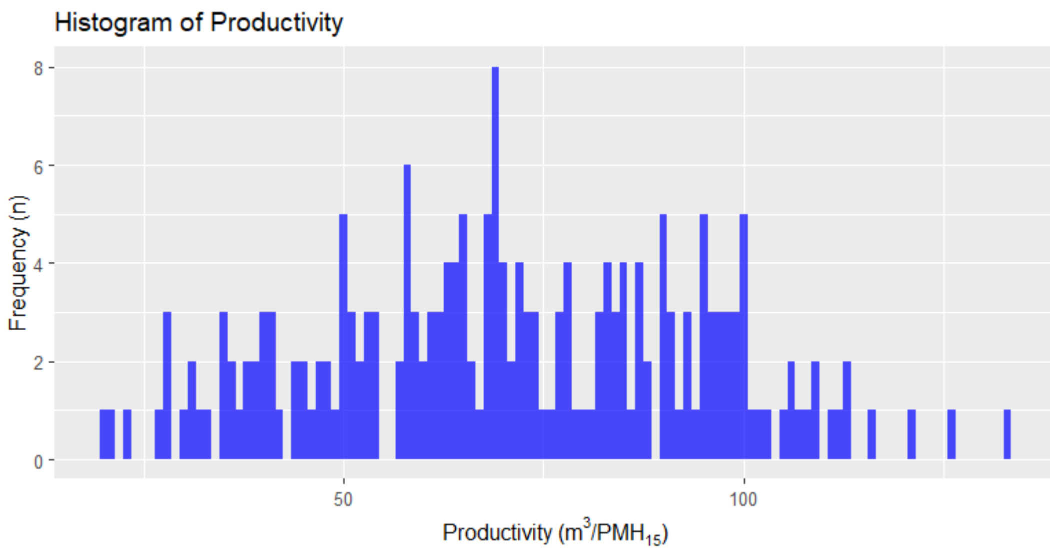


*Figure C.18 Histogram of cutblock-level productivity.*

```
## Generating scatterplot with lm function ----
# Stem Size
ggplot(data, aes(x = AvgStemSiz, y = Prod)) +
  geom_point(color = "black", alpha = 0.6, size = 0.8) +
  geom_smooth(method = "lm", color = "black", se = FALSE) +
  labs(
    title = "Productivity vs. Average Stem Size",
    x = expression("Average Stem Size (m"^3*"/tree)"),
    y = expression("Productivity (m"^3*"/PMH"["15"]*")")) +
  scale_y_continuous(limits = c(0, 150)) +
  theme_classic()
```

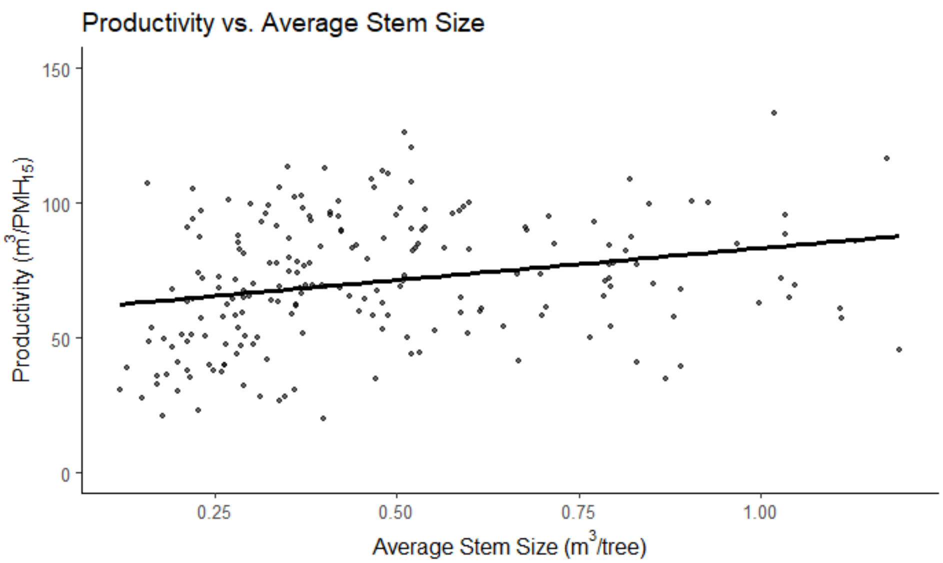


*Figure C.19 Scatterplot showing the relation between Productivity and Average Stem Size at cutblock-level observations. Plot includes linear regression line.*

```
# Volume per ha
ggplot(data, aes(x = VolumePerH, y = Prod)) +
  geom_point(color = "black", alpha = 0.6, size = 0.8) +
  geom_smooth(method = "lm", color = "black", se = FALSE) +
  labs(
    title = "Productivity vs. Volume per ha",
    x = expression("Volume per ha (m"^3*"/ha)"),
    y = expression("Productivity (m"^3*"/PMH"["15"]*")")) +
  scale_y_continuous(limits = c(0, 150)) +
  theme_classic()
```

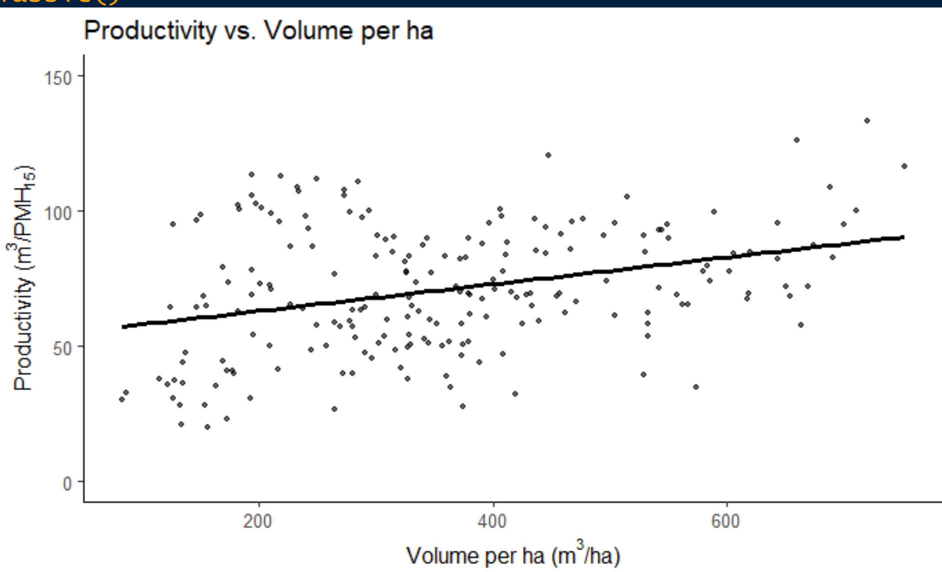


*Figure C.20 Scatterplot showing the relation between Productivity and Average Volume Per Hectare at cutblock-level observations. Plot includes linear regression line.*

```
# Stem Density
ggplot(data, aes(x = AvgStemDen, y = Prod)) +
  geom_point(color = "black", alpha = 0.6, size = 0.8) +
  geom_smooth(method = "lm", color = "black", se = FALSE) +
  labs(
    title = "Productivity vs. Average Stem Density",
    x = expression(paste("Average Stem Density (trees/", ha, ")")),
    y = expression("Productivity (m"^3 * "/PMH"["15"] * ")")) +
  scale_y_continuous(limits = c(0, 150)) +
  theme_classic()
```

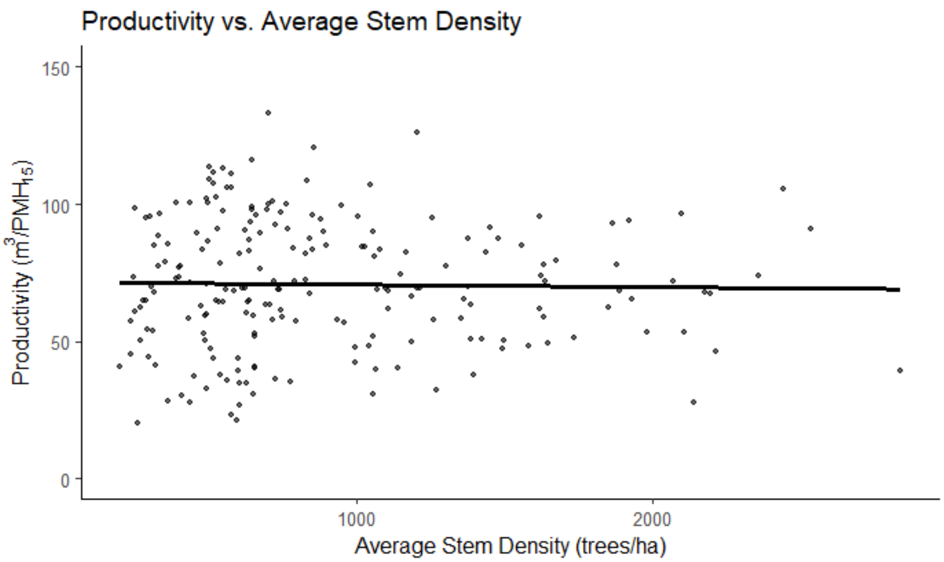


*Figure C.21 Scatterplot showing the relation between Productivity and Average Stem Density at cutblock-level observations. Plot includes linear regression line.*

```
# Ground slope
ggplot(data, aes(x = AvgGroundS, y = Prod)) +
  geom_point(color = "black", alpha = 0.6, size = 0.8) +
  geom_smooth(method = "lm", color = "black", se = FALSE) +
  labs(
    title = "Productivity vs. Average Ground Slope",
    x = expression(paste("Average Ground Slope (", "%",
    y = expression("Productivity (m"^3 * "/PMH"["15"] * ")")) +
  theme_classic()
```

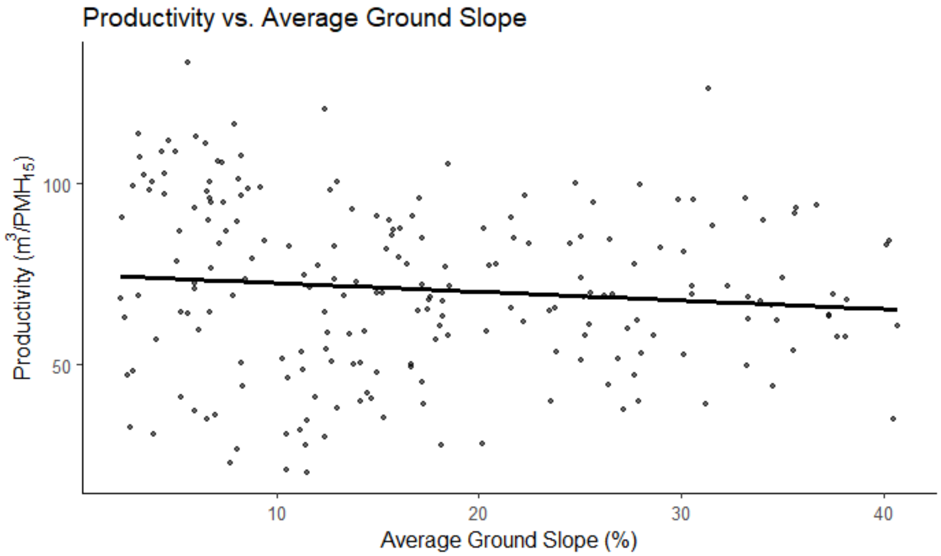


*Figure C.22 Scatterplot showing the relation between Productivity and Average Ground Slope at cutblock-level observations. Plot includes linear regression line.*

```
# Block Size
ggplot(data, aes(x = BlockSiz, y = Prod)) +
  geom_point(color = "black", alpha = 0.6, size = 0.8) +
  geom_smooth(method = "lm", color = "black", se = FALSE) +
  labs(
    title = "Productivity vs. Cutblock Size",
    x = expression(paste("Cutblock Size (ha)")),
    y = expression("Productivity (m"^3 * "/PMH"["15"] * ")")) +
  theme_classic()
```

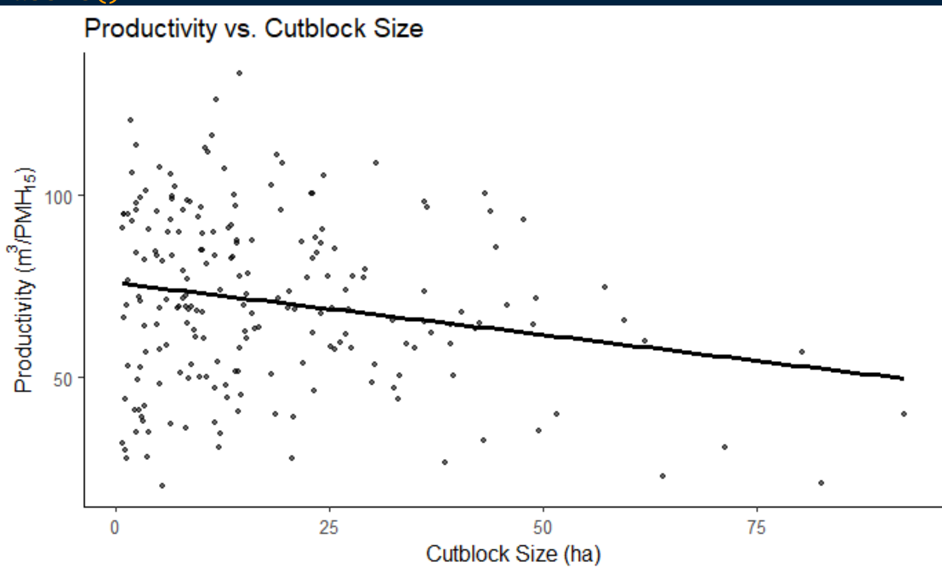


*Figure C.23 Scatterplot showing the relation between Productivity and Cutblock Size at cutblock-level observations. Plot includes linear regression line.*

### C.3.2 lm Linear Model

```
## Fit linear regression model with lm ----
mod_lm_bock <- lm(Prod ~ 0 + AvgStemSiz + VolumePerH + AvgStemDen +
                  AvgGroundS + BlockSiz,
             data = data)
summary(mod_lm_block)

Call:
lm(formula = Prod ~ 0 + AvgStemSiz + VolumePerH + AvgStemDen +
    AvgGroundS + BlockSiz, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-63.593 -13.632   0.918  19.840  62.809

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
AvgStemSiz 90.719705   9.712589   9.340  < 2e-16 ***
VolumePerH  0.022476   0.020947   1.073    0.285
AvgStemDen  0.033924   0.005171   6.560 4.50e-10 ***
AvgGroundS -0.803082   0.201009  -3.995 9.08e-05 ***
BlockSiz   -0.006106   0.105970  -0.058    0.954
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 25.29 on 200 degrees of freedom
Multiple R-squared:  0.888,	Adjusted R-squared:  0.8852
F-statistic: 317.1 on 5 and 200 DF,  p-value: < 2.2e-16

# Confidence intervals
intervals_mod_lm_block <- confint(mod_lm_block, level = 0.95)
intervals_mod_lm_block
                 2.5 %       97.5 %
AvgStemSiz 71.56748779 109.87192144
VolumePerH -0.01882902   0.06378125
AvgStemDen  0.02372736   0.04412134
AvgGroundS -1.19945050  -0.40671265
BlockSiz   -0.21506880   0.20285662

# Compute AIC and BIC for the linear model
AIC_value <- AIC(mod_lm_block)
BIC_value <- BIC(mod_lm_block)

# Print results
print(AIC_value)
[1] 1913.106
> print(BIC_value)
[1] 1933.044


residuals_mod_lm_block <- residuals(mod_lm_block)
fitted_mod_lm_block <- fitted(mod_lm_block)

# Residuals vs. fitted values
plot(fitted_mod_lm_block, residuals_mod_lm_block,
     xlab = "Fitted Values",
     ylab = "Residuals",
     main = "Cutblock Residuals vs Fitted Values")
abline(h = 0, col = "red")
```

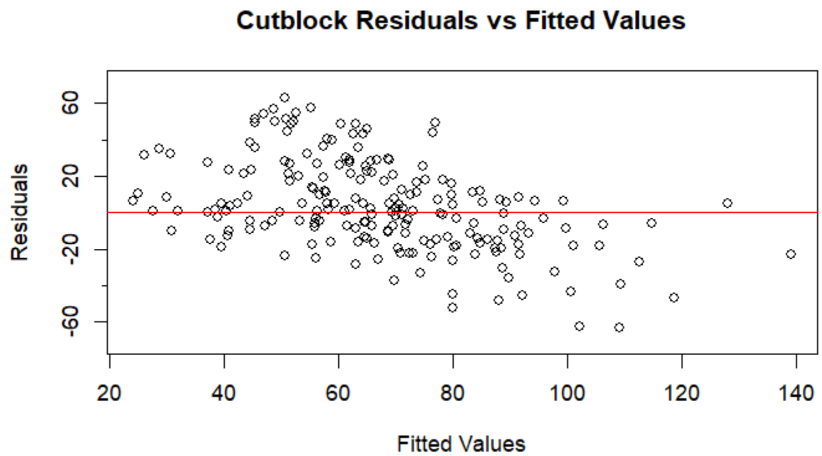


*Figure C.24 Residuals of the linear block-level model plotted against the fitted values.*

### C.3.3 nlme Heteroscedastic Model

```
## Fit heteroscedastic model with nlme at block-level ----
mod_heteroscedastic_block <- nlme::lme(
  Prod ~ 0 + AvgStemSiz + VolumePerH + AvgStemDen + AvgGroundS + BlockSiz,
  random = ~ 1 | Contractor,
  data = data,
  weights = nlme::varIdent(form = ~ 1 | Contractor),
  control = lmeControl(opt = "optim", maxIter = 10000000,
  msMaxIter = 10000000, tolerance = 1e-4) # Iterations)
# Summary of the model
summary(mod_heteroscedastic_block)
Linear mixed-effects model fit by REML
  Data: data
       AIC      BIC    logLik
  1841.416 1960.155 -884.7079

Random effects:
 Formula: ~1 | Contractor
        (Intercept) Residual
StdDev:    16.20965 13.13021

Variance function:
 Structure: Different standard deviations per stratum
 Formula: ~1 | Contractor
 Parameter estimates:
      Alpine Backhoe Services Ltd.          Antler Creek Logging Ltd.
                       1.000000000                        1.129307626
          Best Managed Forest Ltd.              Big Lake Logging Ltd.
                       0.005360172                        1.895919237
      BLUE VALLEY ENTERPRISES LTD.      BLUEHILLS HARVESTING LTD.\r\n
                       0.021574262                        1.564353648
         Bonanza Lake Logging Ltd.         BRP FORESTRY EVOLUTION LTD.
                       2.046260863                        0.011032384
          CHASSE HOLDINGS LTD.\r\n           Cutter Cove Logging Ltd.
                       1.248652218                        0.057557233
           DALCHAKO TIMBER LTD\r\n              ECHO LOGGING LTD.\r\n
                       0.836210341                        0.420511544
      EDGEWATER SOLUTIONS INC.\r\n              Holyoak Holdings Ltd.
                       0.985410069                        1.036381372
           HOTSAW LOGGING LTD.\r\n       IRON PINE CONTRACTING LP\r\n
                       0.005847431                        1.056303341
```

```
               JoR Contracting Ltd.          Jordan River Logging Ltd.
                        0.865279754                        1.291301448
      JRJ LOGGING INCORPORATED\r\n               Kwest Harvesting Ltd.
                        2.152050062                        0.760966885
     LO-BAR LOG TRANSPORT CO. LTD.         PINERIDGE LOGGING INC.\r\n
                        1.350955178                        1.847794688
        R CLAUSON LOGGING LTD.\r\n               RGM HOLDINGS LTD.\r\n
                        0.855430805                        2.400163076
River City Logging Management Ltd.             Strong Back Timber Ltd.
                        0.572602617                        1.969674626
                 Tahtsa Timber Ltd.          Timberstone Logging Ltd.
                        0.009699165                        0.016640943
          Wahkash Contracting Ltd.        Way Key Limited Partnership
                        0.565323770                        1.759833091
Fixed effects:  Prod ~ 0 + AvgStemSiz + VolumePerH + AvgStemDen + AvgGroundS
+      BlockSiz
              Value Std.Error  DF   t-value p-value
AvgStemSiz 49.20571  9.690473 171  5.077740  0.0000
VolumePerH  0.09548  0.017329 171  5.509698  0.0000
AvgStemDen  0.01397  0.004057 171  3.444407  0.0007
AvgGroundS -0.56365  0.141952 171 -3.970720  0.0001
BlockSiz    0.05783  0.066752 171  0.866282  0.3875
 Correlation:
           AvgStS VlmPrH AvgStD AvgGrS
VolumePerH -0.801
AvgStemDen  0.618 -0.735
AvgGroundS -0.240 -0.058 -0.221
BlockSiz   -0.053  0.062 -0.209 -0.116

Standardized Within-Group Residuals:
        Min          Q1         Med          Q3         Max
-2.33029852 -0.60619330  0.00105819  0.77279169  1.89033871

Number of Observations: 205
Number of Groups: 30

# Confidence intervals
intervals_mod_heteroscedastic_block <- intervals(mod_heteroscedastic_block,
                                                 which = "fixed")
intervals_mod_heteroscedastic_block
Approximate 95% confidence intervals

 Fixed effects:
                  lower        est.       upper
AvgStemSiz 30.077353251 49.20570724 68.33406123
VolumePerH  0.061272540  0.09547956  0.12968659
AvgStemDen  0.005966073  0.01397481  0.02198355
AvgGroundS -0.843856756 -0.56365248 -0.28344821
BlockSiz   -0.073937590  0.05782575  0.18958909

> # Compute R² values for mixed model Nakagawa, S., & Schielzeth, H. (2013)
> r2_values <- r.squaredGLMM(mod_heteroscedastic_block)
> # Print R² values
> print(r2_values)
           R2m       R2c
[1,] 0.5094724 0.8056599

residuals_mod_heteroscedastic_block <- residuals(mod_heteroscedastic_block)
fitted_mod_heteroscedastic_block <- fitted(mod_heteroscedastic_block)
```

```
# Residuals vs. fitted values
plot(fitted_mod_heteroscedastic_block, residuals_mod_heteroscedastic_block,
     xlab = "Fitted Values",
     ylab = "Residuals",
     main = "Cutblock Heteroscedastic Residuals vs Fitted Values")
abline(h = 0, col = "red")
```

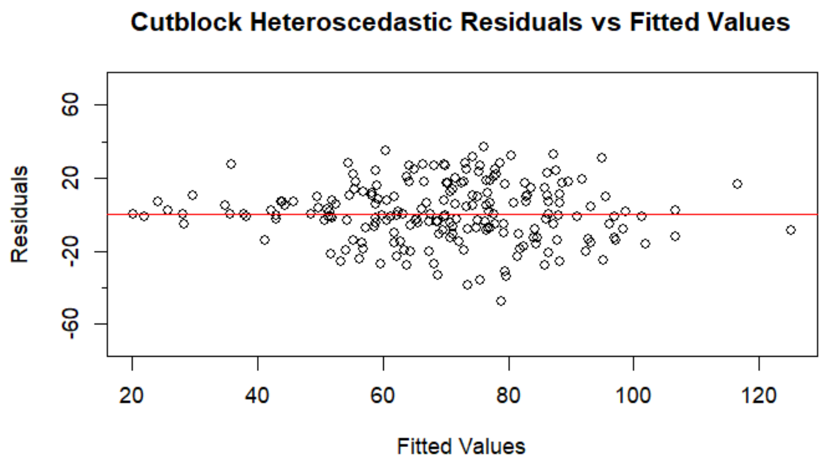


*Figure C.25 Residuals of the heteroscedastic block-level model plotted against the fitted values.*