COMPARATIVE ANALYSIS OF REMOTE SENSING AND GROUND-BASED SURVEYS IN DETERMINING MERCHANTABLE VOLUME OF A BOREAL FOREST STAND

by

Dan A. Guindon

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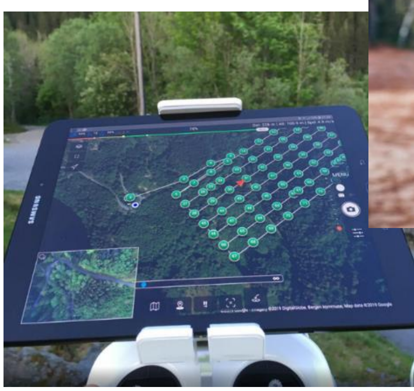

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FACULTY OF NATURAL RESOURCES MANAGEMENT

LAKEHEAD UNIVERSITY

THUNDER BAY, ONTARIO, CANADA

May 2024

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An Undergraduate Thesis Submitted in

Partial Fulfillment of the Requirements for the

Degree of Honours Bachelor of Science in Forestry

(or Degree of Honours Bachelor of Environmental Management)

Faculty of Natural Resources Management

Lakehead University

Thunder Bay, Ontario, Canada

2024

Major Advisor **Second Reader**

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ABSTRACT

Keywords: Forest Volume Estimation, Remotely Piloted Aircraft System (RPAS), Ground survey, LiDAR, STEMS, Bill of Lading (BOL)

Accurate volume estimations are pivotal for effective forest resource management, influencing stakeholders throughout the forestry industry. Traditionally, estimations relied on stem diameter measurements and geometric assumptions. However, advancements in remote sensing have revolutionized volume calculations, offering new possibilities for precision and efficiency. This thesis delves into volume estimations within the Romeo Mallette Forest of Northeastern Ontario’s Boreal Forest, employing a multifaceted approach that includes ground surveys, Ontario Forest Resource Inventory (FRI) data, and Remotely Piloted Aircraft System (RPAS)-based remote sensing. The objectives encompass evaluating the accuracy of FRI data, assessing ground surveys' precision, investigating RPAS. Additionally, the study aims to leverage FPInnovations' Single Tree Metrics and Stand assessment (STEMS), a pre-harvest inventory tool that utilizes consumer-grade RGB imagery from an RPAS, and to scrutinize the variance between estimated volumes and actual mill volumes. The study meticulously evaluates the efficacy of the STEMS algorithm against ground surveys and FRI merchantable volume estimates, utilizing the final Bill of Lading (BOL) as the control measurement. Remarkably, the initial RPAS flight path, harnessing STEMS technology, emerged as the most precise in estimating merchantable volume, yielding 129 m^3/ha compared to the final BOL measurement of 122 m^3/ha. In contrast, ground surveys anticipated 134 m^3/ha, while the FRI data was the only underestimation at 106 m^3/ha. This singular study underscores the potential of STEMS in accurately estimating merchantable volumes in forestry, signaling a significant advancement in volume estimation methodologies.

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ACKNOWLEDGEMENTS

I wish to extend my sincere gratitude to the individuals and organizations whose contributions were instrumental in the completion of this research project. Firstly, I am deeply thankful to my thesis supervisor, Dr. Dzhamal Amishev, for his invaluable guidance, unwavering support, and insightful feedback throughout this journey. I am also grateful to my second readers, Udaya Vepakomma and Bilei Gao, for their expertise and constructive input that greatly enriched the quality of this thesis. Special appreciation is owed to Interfor Timmins, ON, for their generous provision of essential data, without which this study would not have been possible. Additionally, I extend my heartfelt thanks to FPInnovations for their invaluable support and for graciously sharing the necessary data. A special thanks to the Ontario Forest Sector Capacity Building Initiative, funded by the Northern Ontario Heritage Fund Corporation (NOHFC) and FedNor, which enabled this research. Lastly, I am grateful to all individuals who offered their assistance and encouragement. Thank you all for your contributions and support.

INTRODUCTION

The sustainable management of forest resources is imperative for the forestry industry, with accurate measurements of round wood volumes serving as a cornerstone for effective decision-making. These measurements hold significant implications for various stakeholders within the forest ecosystem, including forest managers, owners, harvesting companies, haulers, private purchasers, and processors (Moskalik et al., 2022). Traditionally, estimating the volume of trees in forestry has relied on stem diameter measurements and geometric assumptions, often supplemented with conversion factors to calculate volume and load weight (Moskalik et al., 2022; An & Froese, 2023). However, advancements in technology, particularly in the realm of remote sensing, have introduced new avenues for achieving highly detailed spatial data about forested landscapes.

Technological innovations, such as RPAS-based remote sensing and Light Detection and Ranging (LiDAR), offer unprecedented opportunities to enhance the accuracy and efficiency of volume estimations in forestry operations (An & Froese, 2023). These technologies provide comprehensive insights into the physical surface of objects like trees, facilitating more precise volume calculations compared to traditional methods. In particular, the utilization of LiDAR and RPAS-based techniques has gained prominence due to their ability to deliver quick and detailed assessments of forested areas, thereby mitigating the need for labor-intensive ground surveys, especially in challenging terrain.

The importance of accurate volume estimations is underscored by their pivotal role in the forestry industry, particularly in the context of establishing Annual Work Schedules (AWS). Forest managers are tasked with determining the required quantities of wood from mills, necessitating precise estimations to identify specific forest blocks that can fulfill these demands effectively. Failure to achieve accurate estimations can lead to disruptions in supply chains, impacting both forest management practices and industrial processes.

Against this backdrop, this thesis aims to investigate the accuracy of various methods of volume estimations in a specific forest unit, the Romeo Mallette Forest in Northeastern Ontario. Leveraging publicly available Forest Resource Inventory (FRI) data, ground surveys, and RPAS-based remote sensing techniques, this study seeks to evaluate the effectiveness of different approaches in estimating tree volumes. Furthermore, it endeavors to analyze the variance between these estimations and the volumes documented in the final Bill of Lading (BOL) provided by the mill, thereby contributing to the discourse on optimizing volume estimation methodologies in forestry operations.

The primary objective of this study is to determine the accuracy of volume estimations using various methods, including ground surveys, FRI's data, and a simple RPAS-based remote sensing technique, in the Romeo Mallette Forest in northeastern Ontario's boreal forest. Specifically, the objectives are as follows:

1) Evaluate the accuracy of FRI data in estimating tree volumes within the forest unit.
2) Assess the accuracy of ground surveys, encompassing measurements of mortality, defects, height, and diameter at breast height (DBH), in estimating tree volumes.
3) Investigate the accuracy of FPInnovations' proprietary single-tree-based image processing algorithm (STEMS) in calculating volume based on images acquired from the RPAS.
4) Analyze the degree of variance between volume estimations obtained through different methods and the volumes documented in the final BOL provided by the mill.

Through these objectives, this study aims to contribute valuable insights into the accuracy and efficacy of various volume estimation techniques, thereby informing forest management practices and enhancing operational efficiency in the forestry industry.

We hypothesize that the ground surveys will exhibit the highest overall accuracy in volume estimation when compared to other methods, including FRI data, and RPAS imagery with the incorporation of FPInnovations' STEMS algorithm. This expectation is grounded in the assumption that ground surveys, despite their labor-intensive nature, provide direct and detailed measurements of key parameters such as mortality, defects, and precise height, and DBH measurements which are crucial for accurate volume calculations.

Although RPAS technology provides rapid and extensive aerial coverage, extracting detailed inventory information from RPAS imagery may pose challenges for STEMS volume estimations. Furthermore, the utilization of FRI data, raises concerns due to the absence of Ontario's newest term 2 enhanced FRI (T2 eFRI) program which utilizes an advanced LiDAR systems to derive volume estimates. Additionally, potential limitations associated with image processing algorithms, especially when applied to data obtained from a consumer-grade RPAS, must be considered.

Overall, we hypothesize that ground surveys will demonstrate the highest degree of accuracy in estimating tree volumes within the Romeo Mallette Forest, the FRI data, then STEMS estimate derived from the RPAS imagery. These hypotheses will be empirically tested and analyzed to provide insights into the effectiveness of different volume estimation methods in the context of forestry operations.

LITERATURE REVIEW

History of volume estimations

Volume estimations have played a pivotal role in Canadian forestry practices since the late 19th century. With the acquisition of forestlands through crown grants in 1858 and the subsequent granting of timber rights between 1865-1907 via leases and licenses, the need to identify prime stands containing significant volume became imperative (Parminter, 2000). This period marked the emergence of timber cruising, initially conceived to stake timber claims and facilitate the sale of rights to local mill owners (Parminter, 2000). However, during this era, volume calculations were fraught with speculation due to limited available information, resulting in heavy reliance on guesswork (Parminter, 2000).

In response to the challenges posed by speculative estimations, British Columbia established the Department of Forest, headed by a Chief Forester, to oversee forest inventory activities (Parminter, 2000). A first in Canadian history. The Chief Forester was tasked with developing a comprehensive program to inspect, survey, cruise, and evaluate forest lands within the province, reflecting a recognition of the critical need for accurate forest inventory information (Parminter, 2000). During this period, skilled timber cruisers emerged as key figures capable of generating detailed reports describing available harvest volume, species breakdown, expected timber quality, and development prospects (Parminter, 2000).

These historical developments laid the foundation for the traditional methods still employed in forestry today. Despite advancements in technology and methodologies, the fundamental principles of accurate volume estimation established during this era continue to inform contemporary forest management practices.

Traditional Methods

Traditional ground surveys, often termed timber cruises, utilize various sampling techniques to gather precise inventory data. Among these, fixed-area plots (FAPs) and prism cruising stand out as prominent methods (Keene & Barlow, 2019).

FAPs, including fixed-radius plots, systematically count and record trees within a consistent spatial area, ensuring reliable estimations of the overall tree population (Packard & Radtke, 2007). These plots offer statistical and operational advantages, particularly in estimating total tree numbers (Packard & Barlow, 2007). Unlike Variable Radius Plots (VRPs), which are adept at estimating stand basal area and volume, fixed-radius plots simplify tree tallying, ensuring equal probability of inclusion (Packard & Radtke, 2007).

Prism cruising involves using wedge prisms to identify and tally "in" trees whose refracted section overlaps the non-refracted portion of the main bole (Keene & Barlow, 2019). This method, when multiplied by the basal area factor (BAF) of the prism used during the plot, provides estimates of stand basal area and volume (Keene & Barlow, 2019).

However, traditional ground techniques face challenges in accurately capturing the complex variation in log shapes, sizes, and defects, especially in forests with diverse log lengths (Li et al., 2015). Fixed taper equations, commonly used in traditional methods, may lack precision, and their reliance on DBH and height relationships can lead to less accurate estimates (Li et al., 2015).

Moreover, traditional methods are labor-intensive, time-consuming, and prone to large errors, particularly in commercial volume estimates (Dassot et al., 2011). To improve volume estimation accuracy, various formulae such as Smalian, Bruce, Huber, and Newton are commonly used (Li et al., 2015). Each formula has distinct characteristics and limitations, with Smalians tendency to overestimate volume due to its assumption of a paraboloid log shape being noteworthy (Li et al., 2015).

Formulae for calculating volumes

Once the critical data has been collected from a traditional ground survey, a formula to calculate the volume will have to be selected. The most commonly used formulae for estimating merchantable volume include Smalian, Bruce, Huber, Newton, and Conical each offering distinct characteristics and limitations (Li et al., 2015).

Smalian's formula tends to overestimate volume due to its assumption of a paraboloid log shape (Li et al., 2015). Bruce's butt log formula, a modification of Smalian's, adjusts weights in the large-end-diameter (LED) and small-end-diameter (SED) to account for changes in the butt portion (Li et al., 2015). Huber's formula assumes that the average cross-sectional area of the tree is at the midsection, which may not hold true for every tree (Li et al., 2015). Newton's formula is considered the most accurate but requires measurements of LED, SED, and mid-length diameter (MED) (Li et al., 2015). Despite its tendency to overestimate volume, Smalian's formula remains widely used (Li et al., 2015).

Alternatively, the conical formula offers a simpler approach, particularly useful when less data is available. However, choosing the appropriate formula can be complex, as it requires consideration of factors such as log shape, data availability, and desired accuracy.

The complexity of selecting proper volume calculation methods underscores the need for improved techniques in forestry inventory. Remote sensing, for instance, can provide valuable insights by predicting volumes through analysis of aerial or satellite imagery. These advanced techniques offer the potential to enhance accuracy, efficiency, and sustainability in forest management practices, thereby mitigating the limitations associated with traditional ground-based methods.

Remote sensing

Remote sensing was a technology developed around 1960 taking aerial image a step further by utilizing methods and technologies for sensing the earths surface (Moore, 2009). Remotes sensing techniques harness electromagnetic energy to measure the physical properties of distant objects, mixing both traditional photography with more advanced methods of utilizing various parts of the electromagnetic spectrum (Moore, 2009).

The historical origins of remote sensing backed to photography, with subsequent developments tied to World War II, where the emergence of radar, sonar, and thermal infrared detection systems came to popularity (Moore, 2009). Remotes sensing has become a fundamental tool internationally, with applications spanning from groundwater exploration, mapping snowfields, delineating flood areas, and calculating inventories of natural resources (Moore, 2009).

The most notable advantage to remote sensing technologies is the ability to collect data at a relatively cheap cost (Moore, 2009). These tools became even more valuable when incorporated with and aerial object like a plane, satellites and now RPAS (Moore, 2009).

Aerial imagery emerged in 1858, thanks to a French balloonist Gaspard-Felix Tournachon, and it involved using balloons and kites to capture images from elevated perspectives (Kraetzig, 2020). Over time the process evolved into capturing images from an airborne platform, such as a RPAS or plane (Kraetzig, 2020). Natural resource management has long depended on the use of aerial imagery, as it's been a critical tool for FRI in Ontario, as well as being used for monitoring and assessing resources (Hall, 2003).

These images serve as a valuable resource, commonly employed for manual delineation and various other applications (Hall, 2003). Aerial imagery doesn't require the costly scanning required to function remote sensing systems, making them more efficient for mass landscape analysis as aerial imagery continues to excel in terms of spatial resolution, data storage and hardcopy output capabilities (Hall, 2003).

Requirements for photogrammetry algorithm to produce accurate estimates

To ensure the accuracy and reliability of forest inventory estimates, photogrammetry algorithms must meet several key requirements. Firstly, high-quality imagery is essential, with images needing to be of sufficient resolution and clarity to enable precise measurements of tree dimensions and structures (Mulverhill et al., 2019). Additionally, there should be adequate image coverage to capture the entire tree canopy and stem from multiple angles, minimizing occlusions and ensuring comprehensive data acquisition (Mulverhill et al., 2019). Incorporating known scale references, such as fixed scale bars within the image frame, is crucial for accurately scaling the resulting point clouds (Mulverhill et al., 2019).

These references provide a means of calibrating the photogrammetric reconstruction, enabling precise measurements of tree dimensions (Mulverhill et al., 2019). Moreover, photogrammetry algorithms should be optimized to handle the complexities of forest environments, including variations in lighting conditions, occlusions, and irregular tree shapes (Mulverhill et al., 2019). Advanced algorithms capable of robust feature detection, point cloud generation, and geometric modeling are necessary for accurate tree dimension estimation (Mulverhill et al., 2019).

Validation and calibration procedures are essential to assess the accuracy and reliability of photogrammetry algorithms. Validation involves comparing algorithm outputs with ground-truth measurements to ensure accuracy, while calibration procedures refine algorithm parameters for specific forest conditions and tree species (Mulverhill et al., 2019). Cost-effectiveness and accessibility are also crucial considerations, with photogrammetry algorithms needing to utilize affordable hardware and software solutions to enable widespread adoption by forest managers, researchers, and practitioners (Mulverhill et al., 2019). By meeting these requirements, photogrammetry algorithms can provide accurate and efficient means of estimating forest inventory parameters.

Ontario Forest Resource Inventory (FRI)

Ontario's FRI program, established in 1946, represents a pioneering effort aimed at meticulously identifying and mapping forest stands across the province (MNR, 2023). Initiated by the Ministry of Natural Resources (MNR), this comprehensive endeavor has been pivotal in gathering crucial data pertaining to the composition, distribution, and age structure of Ontario's diverse forest ecosystems (MNR, 2023).

Initially launched with a 20-year cycle, the FRI program evolved over time, driven by advancing technological capabilities and evolving resource management needs (MNR, 2023). Subsequently, the inventory cycle was halved to a more frequent 10-year interval, allowing for more timely and accurate assessments of Ontario's forest resources (MNR, 2023).

Covering over 555,000 square kilometers of forest and wetland areas, Ontario's FRI holds significant legal importance under the Crown Forest Sustainability Act (1994) (MNR, 2023). It serves as a cornerstone for informed resource management and land use decision-making processes, ensuring sustainable utilization of forest resources (MNR, 2023).

Traditionally reliant on a combination of field surveys and aerial photo-imagery, the FRI has embraced technological advancements to enhance precision and efficiency. Presently, advanced technologies such as Single-Photon LiDAR and optical imagery are employed for comprehensive assessments (MNR, 2023). This involves sophisticated data processing to generate terrain and canopy models, followed by rigorous quality assessment procedures (MNR, 2023).

The FRI provides invaluable information on tree species composition, height, age, and density, facilitating informed resource management decisions and sustainable land use practices (MNR, 2023). These data sets not only support provincial mandates but also meet federal and international reporting requirements, underscoring their significance on multiple levels (MNR, 2023).

Every 10 years, the Ministry of Natural Resources creates a new forest management plan, wherein updated inventory data from the FRI plays a crucial role (MNR, 2023). Compliance with the Crown Forest Sustainability Act (1994) mandates adherence to the requirements outlined in the Act, ensuring responsible forest management practices (MNR, 2023).

The FRI continuously undergoes refinement and enhancement through consultations and product development efforts. Draft FRI Packaged Product data sets are provided for consultation and product development purposes, with attributes and algorithms subject to evolution over time

(MNR, 2023). A final version of the FRI structure and content will be made available after the requisite consultations are complete (MNR, 2023).

To enhance accessibility and utility, the FRI data sets are now available through a web service, facilitating visualization and geoprocessing. This expanded accessibility ensures broader engagement and utilization of the invaluable data resources provided by Ontario's Forest Resource Inventory program (MNR, 2023).

Light Detection and Ranging (LiDAR)

LiDAR, the optical counterpart of radar, operating off the principle of emitting electromagnetic pulses towards objects, and measuring the time it takes for pulses to return, allowing for precise distance calculations (Moore, 2009; Bogue, 2022). LiDAR systems composed of an infrared (IR) laser source and a silicone avalanche photodiode detector, in combination the system scans the laser beam in two dimensions, LiDAR then generates a point-cloud into 3D imagery (Bogue, 2022).

LiDAR is an active remote sensing system, that generates its own energy, specifically light, to measure objects on the ground (Wasser, 2023). It works by emitting laser lights that travel to the ground and reflects off surfaces like buildings and tree branches (Wasser, 2023). The reflected light returns to the LiDAR sensor, where it's then recorded (Wasser, 2023).

The system calculates the time taken for the emitted light to travel to the ground and back, using this information to determine distance and subsequently convert it into elevation (Wasser, 2023). Key components include a GPS for location identification and an Inertial Measurement Unit (IMU) for determining the plane's orientation in the sky (Wasser, 2023).

For the context of forest management in Ontario, LiDAR technology is being introduced as a significant advancement in the forest inventory process (Bilyk et al., 2020) The implementation of Term 2 eFRI (T2 eFRI) in 2018 marked a historic shift, as it represents the most substantial change in forest inventory in Ontario since the inception of aerial photography in 1926 (Bilyk et al., 2020).

This innovative approach utilizes SPL across all the Sustainable Forest Licenses (SFLs) in Ontario (Bilyk et al., 2020). This technique differs from conventional LiDAR, as SPL employs a single pulse split into 100 beamlets, enabling more efficient coverage of larger areas (Bilyk et al., 2020). Additionally, SPL uses the green portion of the electromagnetic spectrum, providing advantages such as potential assessment of near-shoreline riparian areas. LiDAR systems record the return of light energy in two ways, Discrete Return LiDAR records individual points for peaks in the waveform curve, known as returns (Wasser, 2023).

It typically records 1-4 returns per laser pulse. Full Waveform LiDAR, on the other hand, captures a distribution of returned light energy, offering more complex data but potentially capturing more information (Wasser, 2023). Comparison LiDAR data, whether in discrete or full waveform, are commonly stored as LiDAR point clouds in .las format, supported by ASPRS (Wasser, 2023). Another format, .laz, is a compressed version of .las, developed by Martin Isenberg (Wasser 2023).

LiDAR data attributes vary based on the collection and processing methods. Each point has X, Y, and Z values. Intensity represents recorded light energy, classification, an additional step, categorizes points based on the reflected object type, such as "vegetation" for trees or "ground" for terrain (Wasser, 2023). Some datasets classify as "ground/non-ground" or specify infrastructure reflections, while others categorize vegetation types (Wasser, 2023). Understanding these attributes is an important factor for utilizing LiDAR data.

Challenges to LiDAR volume estimates

LiDAR technology has become indispensable in forest inventory and canopy characterization (Dassot et al., 2011). However, its effectiveness hinges upon careful consideration of measurement patterns and device specifications aligned with study objectives (Dassot et al., 2011). Commercially available LiDAR sensors typically have a small footprint characterized by small diameter beams, which can pose challenges in capturing the tops of trees (Suarez et al., 2005). This limitation can impact the reconstruction of a three-dimensional tree canopy structure, 19 necessitating adjustments in measurement density to achieve accurate estimations (Suarez et al., 2005). Spatial resolution requirements for accurately retrieving the morphology of individual trees are suggested to be around 10 cm (Suarez et al. 2005).

Furthermore, Airborne Laser Scanning (ALS) provides pointwise sampling rather than full area coverage, necessitating interpolation of laser data for conversion to an image. However, the gridding process introduces errors into the tree canopy model (TCM) due to interpolation method and grid spacing choices, influencing canopy dimensions and tree height estimates (Suarez et al. 2005; White et al., 2014). Accurate estimation of TCM dimensions relies on a good approximation of the ground cover beneath the canopy. In small-footprint LiDAR systems, only the gaps in canopy cover allow laser shots to reach the ground, requiring spatial interpolation techniques for terrain modeling (Suarez et al., 2005).

Similar to other remote sensing approaches weather conditions also pose significant limitations, as adverse weather like heavy rain, fog, and low hanging clouds can affect LiDAR pulses due to refraction, while direct sunlight can cause data acquisition failures, especially in infra-red sensors (Suarez et al., 2005; Guo et al., 2022; Malta et al., 2023). Vegetation density also impacts LiDAR pulse penetration, potentially hindering accurate ground readings (Suarez et al., 2005; Arkin et al., 2021).

Moreover, ALS often intercepts a substantial number of LiDAR returns, limiting the amount of information obtained, particularly regarding understorey vegetation, and hindering a comprehensive depiction of forest state (Suarez et al., 2005; Arkin et al., 2021). Cost is another significant challenge, as LiDAR acquisition and processing expenses can be considerable.

Equipment costs, licensing fees, and human resources add to the financial burden, making widespread adoption challenging (Tassel, 2021; Arkin et al., 2023). Additionally, data storage and processing generate large amounts of high-resolution point clouds, requiring specialized knowledge and skills, which can be a barrier for individuals without expertise (Suarez et al., 2005; Arkin et al., 2021; Malta et al., 2023).

Ability to capture 3D

LiDAR technology operates by transmitting and receiving up to 500,000 pulses of laser light per second, providing an exceptional level of detail for creating high-resolution 3D depictions of forests (Wulder et al., 2012). Through this rapid pulse rate, LiDAR captures reflective objects with precision, enabling the generation of detailed maps that vividly represent the three-dimensional structure of the forest environment (Wulder et al., 2012).

Forest structure and wood fibre attributes can also be depicted in the 3D imagery allowing for various wood fiber properties like wood density and fibre dimensions to be identified (Wulder et al., 2012). This information on fiber quality adds a new dimension to the current Forest Resource Inventory, which already consists of various tree and landform attributes (Wulder et al., 2012). Furthermore, the emitted light pulses can penetrate the tree canopy through gaps, allowing for both vertical and horizontal forest structure (Guo et al. 2022). Allowing for direct measurements of various forest structures.

LiDAR outperforms other remote sensing systems in predicting forest structural attributes, with high sampling density, which enables a three-dimensional analysis, and facilitating the detection of individual tree crowns and their dimensions (Suarez et al., 2005). Researchers have successfully estimated stem diameters and retrieved vertical forest canopy and understory vegetation structures using LiDAR data (Suarez et al., 2005). Techniques like canopy-based quantiles have been employed to estimate mean tree heights at the stand level, providing valuable insights into stand parameters such as mean height, canopy depth, or leaf area index (LAI) (Suarez et al., 2005).

Remotely Piloted Aircraft Systems (RPAS)

Over the past decade, the integration of RPAS with machine learning techniques has gained significant traction in the forestry sector (Eugenio et al., 2021). Eugenio et al. (2021) applied a systematic approach to identify relevant scientific articles published between 2000 and 2019, utilizing databases such as Web of Science (WoS) and Scopus (Eugenio et al., 2021). Criteria for article selection included relevance to RPAS applications in forest areas, integration of machine learning techniques, and availability of data on parameters such as sensor types, algorithms used, and application areas (Eugenio et al., 2021).

Eugenio et al. (2021) reviews a range of machine learning algorithms commonly applied in remote sensing for forestry applications, including Random Forest (RF), Neural Networks

(NNs), Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbor (k-NN), and Logistic Regression (LR) (Eugenio et al., 2021). Each algorithm has strengths, limitations, and typical applications in forestry (Eugenio et al., 2021).

A total of 57 articles met their selection criteria, indicating a significant increase in publications on RPAS applications in forestry from 2017 to 2021 (Eugenio et al., 2021). RF emerged as the most frequently used algorithm, followed by NNs and SVM, with RGB sensors being the predominant choice for RPAS platforms, followed by multispectral and LiDAR sensors (Eugenio et al., 2021).

Applications of RPAS and machine learning were found to be used in forestry, for the purpose of forest inventory and measurement, plant health assessment, ecology, conservation, and land use/ land cover analysis (Eugenio et al., 2021). Forest Inventory and Measurement: RF is widely utilized for growth rate prediction, biomass estimation, species classification, and forest restoration assessment (Eugenio et al., 2021). Plant Health: Machine learning techniques aid in early insect attack prediction, severity estimation of damage caused by beetle attacks, and canopy cover monitoring (Eugenio et al., 2021).

Ecology and Conservation: NNs are employed for deforestation monitoring, post-fire vegetation loss assessment, and palm tree detection (Eugenio et al., 2021). Land Use and Land Cover Patterns: Algorithms like RF are instrumental in urban vegetation classification, tree and herbaceous vegetation separation, and gross primary productivity monitoring (Eugenio et al., 2021). Other Applications: Machine learning algorithms are applied to seedling planting inventory, tree stump detection and segmentation, and mounds identification in forest sites (Eugenio et al., 2021).

Their review identified several challenges in the integration of RPAS and machine learning, including high computational costs, segmentation scale determination, spectral heterogeneity, and the need for improved model accuracy and real-time detection features (Eugenio et al., 2021). Eugenio et al. (2021) states that addressing these challenges and leveraging all the opportunities that RPAS presents with machine learning integration will be important in advancing forest monitoring and management practices (Eugenio et al., 2021).

Challenges and Variations in Estimating Timber Volumes

Estimating timber volumes presents challenges influenced by various factors, as highlighted in studies by Keys and McGrath (2002). Existing volume tables, based on tree height and diameter at breast height (DBH), may not universally represent geographical and climatic variations, leading to inaccuracies in volume measurements. Furthermore, differences in wood density among species and the impact of harvesting systems on usable wood volumes add complexity to estimation processes (Keys & McGrath, 2002).

Accurate volume estimations are crucial for informed forest management decisions, contributing to harvest forecasts, forest fire fuel load predictions, and assessments of forest productivity and carbon storage (GC, 2022). These estimations empower decision-makers with comprehensive insights, enabling holistic forest management approaches that balance ecological health, economic sustainability, and environmental conservation (GC, 2022).

Differences in growth patterns between softwood and hardwood

Hardwood and softwood trees exhibit distinct growth patterns, influenced by their reproductive mechanisms and ecological roles. Hardwood trees, characterized by deciduous shedding of leaves, grow more slowly, resulting in denser wood suitable for various applications such as furniture and flooring (Cwynar, 2021; Laver, 2022). In contrast, softwood trees, which retain their needles year-round, grow faster, producing lighter and less dense wood primarily used in construction and structural applications (Cwynar, 2021; Laver, 2022).

Understanding the density variations between hardwoods and softwoods is essential for accurate volume estimation in forestry (Canning, 2023). Hardwoods contribute significantly to total forest volume due to their higher densities, while softwoods, being less dense, are more prevalent in forests but contribute differently to overall volume (Canning, 2023).

Impact of Growth Characteristics on Volume Estimation

Tree growth characteristics, including tapering, forking, leaning, irregular shapes, buttressing, stem splitting, and variation in growth rates, significantly influence volume estimation in forestry (West, 2015). Tapering of tree trunks requires measuring diameter at various heights to account for volume distribution accurately. Additionally, factors such as forking, leaning, and irregular shapes necessitate precise measurements to avoid underestimation. Variation in growth rates across different parts of the tree also impacts volume distribution and shape, requiring consideration during estimation processes (West, 2015).

Bill of Lading (BOL)

A BOL is a legal document issued by a carrier to a shipper, detailing the type of load (species, etc.), quantity of goods, the location the load was loaded at such as block ID, forest unit etc., and the destination of the goods (Tarver, 2023). It serves multiple functions, acting as a document of title, a receipt for the shipped products, and a contract outlining the terms and conditions of transportation (Tarver, 2023). This document must accompany the shipped goods through out the entire journey, as they are signed by authorized representatives from the carrier (harvesting contractor), shipper (hauling company), and receiver (lumber mill) (Tarver, 2023). Properly managed BOLs help track shipments to their origin, allowing for proper certifications to be stamped on the final product (SFI, CSI etc.) (Tarver, 2023).

Previous research on various estimation methods

Ground surveys

Nakajima et al. (1996) investigated the accuracy of four ground survey methods used for estimating forest stand values. The methods under investigation are point sampling (PS), line sampling (LS), circular plot (CP), concentric circular plot (CCP), for estimating the current values of stems, basal area, and volume per hectare (Nakajima et al. 1996). Data was collected from the Takakuma Experimental Forest in Kagoshima Prefecture, Japan, on two occasions (Nakajima et al., 1996). The methods were evaluated for their utility in continuous forest inventory (CFI) for forest management (Nakajima et al., 1996).

Each method was systematically compared based on their accuracy in estimating forest parameters. For PS and LS, a basal area factor of 4 was utilized, while CP had a fixed-radius plot with a radius of 6 meters (Nakajima et al., 1996). CCP employed two concentric circles with radii of 5 and 10 meters, corresponding to different plot sizes (Nakajima et al. 1996). The sampling intensity was set at 12 samples, and the systematic sampling process was applied 10 times for each method (Nakajima et al., 1996).

Results showed variations in accuracy across different variables. CCP demonstrated slight superiority over the other methods for estimating basal area and volume, while CP was slightly better for estimating the number of stems (Nakajima et al., 1996). However, no significant differences were observed in sampling errors among the four methods. Therefore, the selection of the most appropriate method should consider factors beyond sampling error, such as cost and suitability to stand conditions (Nakajima et al., 1996). Highlighting the importance of considering individual stand characteristics, such as structure and topography, and purpose when choosing a ground-survey method.

Terrestrial photography using photogrammetry methods

Another study conducted by Malta et al. (2023) introduces a method for accurately estimating the diameter, total height, and volume of *Pinus pinaster* (maritime pine) trees from terrestrial photographs collected using a Sony Nex-5 with a 18-55 mm lens. Species like *Pinus pinaster* are crucial in Mediterranean forests for wood production and reforestation efforts. This method involves placing reference targets on the trees of known dimensions and using a deep learning neural network, specifically Mask R-CNN, to extract the tree trunk and targets from the background (Malta et al., 2023).

The dimensions of the trunk are then estimated based on the dimensions of the targets, resulting in less than 10% estimation errors for diameter, height, and volume (Malta et al., 2023). The research methodology involved selecting the Mask-RCNN deep learning model for its ability to perform object detection and instance segmentation, enabling the detection of pine trees and targets in images and defining their contours (Malta et al., 2023). Various measurements, including total height and tree diameters, were taken using both destructive and non-destructive methods (Malta et al., 2023).

The data analysis involved calculating the error in estimating the tree's diameter, height, and volume using the Mask-RCNN model (Malta et al., 2023). The results indicated that there were no significant differences between the measured and estimated values of DBH, height, and volume (Malta et al., 2023). The quality of the masks generated by the Mask-RCNN model was found to be very high, with accuracy close to 100% in terms of tree coverage.

Tree diameter estimation using the Mask-RCNN model resulted in an average error of approximately 4%, while tree height and volume estimations also showed promising results, with errors within acceptable ranges (≤10%) (Malta et al., 2023). Offering a time-efficient and cost-effective alternative to traditional measurement methods for estimating tree volume, particularly for small forest owners (Malta et al., 2023). The Mask-RCNN model demonstrated high accuracy in estimating tree biometric characteristics from photographs, with potential applications in sustainable forest management practices (Malta et al., 2023).

RPAS using photogrammetry

Research conducted by Young et al. (2022) explored the utilization of RPAS imagery and photogrammetry for estimating forest metrics, especially in structurally complex conifer forests. Their study investigated the influence of various parameters, such as flight altitude, gimbal pitch, and image overlap, on the accuracy of forest metric estimation. Higher flight altitudes, typically around 120 meters, combined with adequate image overlap have been identified as contributing to better tree mapping accuracy (Young et al., 2022).

Moreover, Young et al. (2022) delved into different photogrammetry processing techniques to create accurate 3D representations of forest environments. Techniques such as generating canopy height models (CHMs) with appropriate upscaling and employing variable window filters for tree detection have been shown to enhance accuracy (Young et al., 2022). Additionally, various tree detection algorithms, including CHM-based Variable Window Filter

(VWF) methods, were evaluated for their effectiveness in identifying individual trees within RPAS-derived imagery (Young et al., 2022).

These algorithms play a critical role in producing accurate tree maps, with certain methods consistently demonstrating superior performance based on accuracy metrics like the F score (Young et al., 2022). Furthermore, Young et al. (2022) have compared RPAS-derived tree maps with ground reference maps created through traditional field survey methods to validate accuracy and understand technology strengths and limitations. Moreover, researchers have developed methods for accurately measuring tree heights using RPAS-derived imagery and CHMs, despite inherent biases the mean absolute height error was relatively small at 1.8 meters or 9% of tree height (Young et al., 2022). The study's algorithm for matching SfM-detected trees with ground-measured trees showed that the mean height difference was only 9%, suggesting accurate matching overall. (Young et al., 2022).

RPAS using LiDAR

A study conducted by Arkin et al. (2021), explores the potential of using high-density LiDAR point clouds obtained from RPAS to characterize forest canopy fuels at the individual tree level. It introduces a novel automated method to detect and quantify live crown fuels within trees by analyzing the density and vertical arrangement of LiDAR points. The research compares results from RPAS LiDAR point clouds with manual measurements derived from ground-based LiDAR point clouds in a dry forest system in British Columbia (Arkin et al., 2021).

The findings demonstrate strong agreement between the automated method and manual measurements, indicating RPAS LiDAR's potential for accurately characterizing crown fuels across large areas (Arkin et al., 2021). The methodology involves initial point cloud processing, individual tree segmentation, live branch cluster extraction and analysis, validation, and accuracy assessment (Arkin et al., 2021). Validation data collected from ground-based LiDAR point clouds support the reliability of the automated method (Arkin et al., 2021).

The study's accuracy assessment involves cluster matching, cluster-level validation, and tree-level validation, revealing favorable trends in cluster matching accuracy and agreement in cluster-level metrics (Arkin et al., 2021). However, variability is observed in tree-level metrics, specifically within lower crown features, due to differences in point cloud quality and collection methods between RPAS LiDAR and ground-based LiDAR (Arkin et al., 2021).

Overall, the research highlights RPAS LiDAR's capability to accurately characterize crown fuels within individual trees, providing valuable insights for wildfire behavior modeling and forest management strategies (Arkin et al., 2021). It’s limitations in capturing lower levels of canopy limits it’s potential in accurately estimating volume.

Aircraft with LiDAR

White et al. (2014) produced a study using a fixed-wing aircraft to collect ALS data for the use of enhancing their forest inventory. The study focuses on the Hinton Forest Management Area in Alberta, Canada, aiming to develop an enhanced forest inventory using ALS data and validate the estimates against post-harvest metrics (White et al., 2014).

The research employs ALS data and an area-based approach, utilizing ground reference data collected through the permanent growth sample (PGS) program (White et al., 2014). ALS data is processed to compute canopy height and density metrics, and a Random Forest (RF) model is developed to estimate coniferous merchantable volume (White et al., 2014).

Validation of the ALS-based estimates is conducted using weight-scale data (White et al. 2014). Weight scaling is a method used for estimating timber volume based on weight-to-volume ratios (White et al., 2014). In the Hinton FMA, 272 coniferous forest stands were harvested between 2008 and 2010, with merchantable weight scale volumes calculated based on cut-to length harvesting practices (White et al., 2014). These weight scale estimates were used as a reliable, industry-relevant source for validating the estimates derived from ALS data and cover type adjusted volume tables (White et al., 2014).

With results showing that conventional methods tend to underestimate coniferous merchantable volume, while ALS-based estimates provide a closer match to post-harvest measurements (White et al., 2014). Comparisons between ALS-based and conventional estimates relative to weight scale data showed that ALS-based estimates overestimated by 0.6%, while conventional methods underestimated by 19.8% (White et al., 2014). The study highlights the accurate estimates of ALS-based estimates when incorporating reliable weight-scale calculations.

Terrestrial LiDAR (TLS)

In another study conducted this time by Panagiotidis and Abdollahnejad (2021) the goal was also to accurately determine the merchantable height and diameter of trees using TLS data, focusing on the random sampling consensus method (RANSAC) for stem modeling. Using TLS data from two plots containing both deciduous and coniferous trees and found that the RANSAC method performed well with low bias and high accuracy for both tree types (Panagiotidis & Abdollahnejad, 2021).

Additionally, they observed a high correlation between their proposed method and actual log lengths, as well as the ability to analyze stem curvature changes at different heights

(Panagiotidis & Abdollahnejad, 2021). This study highlighted the applicability and efficiency of TLS in forest inventories, reducing reliance on conventional field methods (Panagiotidis & Abdollahnejad, 2021).

Building upon previous research emphasizing the importance of accurate forest inventories for sustainable forest management, and showing traditional methods often result in biased estimations, necessitating research into a more reliable technique (White et al., 2014; Panagiotidis & Abdollahnejad, 2021; Malta et al., 2023).

Panagiotidis & Abdollahnejad (2021) found that previous studies have shown the effectiveness of TLS in various forest structural metrics. However, challenges in extracting forest attributes from TLS data and data acquisition protocols persist (Panagiotidis & Abdollahnejad, 2021). To address these limitations, Panagiotidis & Abdollahnejad (2021) used dense TLS point clouds with the RANSAC method to extract merchantable volumes of European oak and Norway spruce trees.

Results showed a high correlation between estimated and measured merchantable volume for both deciduous and coniferous trees (Panagiotidis & Abdollahnejad, 2021). Although the RANSAC method slightly overestimated merchantable volume, the difference was negligible and statistically insignificant for coniferous trees (Panagiotidis & Abdollahnejad, 2021). Analysis revealed a significant relationship between log lengths and bias, suggesting that longer logs led to greater overestimation (Panagiotidis & Abdollahnejad, 2021).

MATERIALS AND METHODS

Location selection

The research site within the Romeo Mallette Forest was chosen based on the 2023/24 Annual Work Schedule (AWS). Block 483 was selected due to its strategic placement along the Gogama Unit Road, a primary branch road known for its accessibility, facilitating easy navigation and data collection efforts. Initially encompassing a total area of 95.84 hectares, subsequent harvesting revealed that only 79.89 hectares had been harvested. Consequently, all volume calculations based on volume per hectare were adjusted by multiplying them by 79.89 to accurately determine their total volumes.

Site characteristics

The selected research area (figure 1), encompasses a total land area of 95.84 hectares. This site is classified under specific silviculture ground rules. Specifically, it falls within the category of Mix Hardwood Class Two (MH2), incorporating extensive silviculture practices classified as Class One (EXTN1). Furthermore, the future forest to be re-established at this site is anticipated to primarily consist of Poplar Class One (PO1) species.

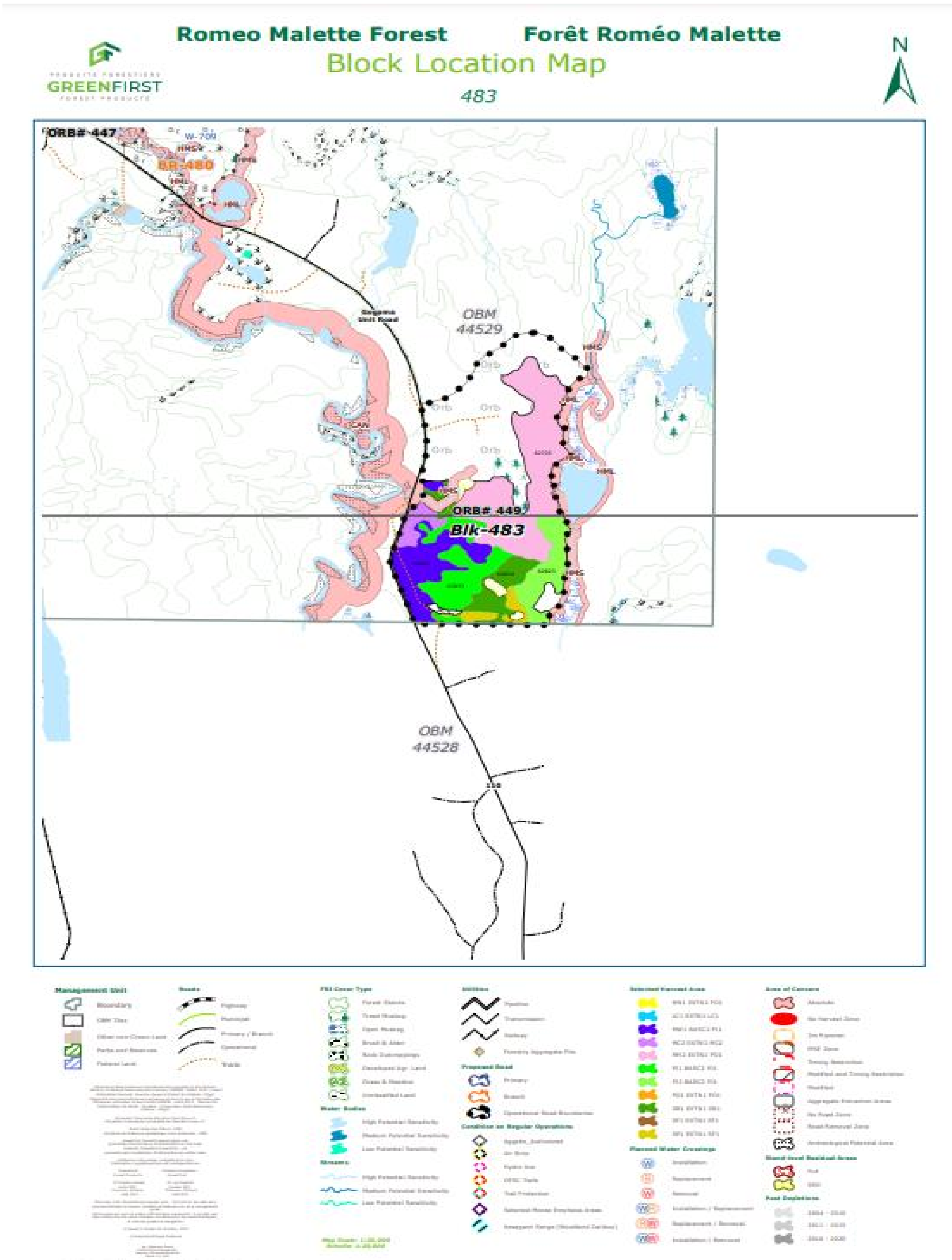

Figure 1. Illustration of the selected forest block.

FRI DATA

The FRI data used in this study was obtained through collaboration with one of the stakeholders of the forest license. It should be noted that the Romeo Malette Forest is one of the only forest management units in Ontario that has been subjected to Ontario's T2 eFRI resulting in the acquisition of high-resolution data for forest analysis and management. The LiDAR imagery can be found on (https://geohub.lio.gov.on.ca/maps/lio::forest-resource-inventory-term-2-t2-2018-2028/about). The research utilized a combination of ground surveys and aerial imagery to gather FRI data for volume estimates, as the volume estimates using T2 eFRI have not yet been produced and likely will not be available until 2028.

GROUND SURVEY

Ground surveys were undertaken to assess the natural stand conditions, investigate tree species distribution and composition, and document relevant tree-level attributes within the study area. To achieve this, circular ground plots covering an area of 400 square meters, with an 11.28-meter radius, were systematically established throughout the research site. The sampling intensity is 0.375%.

A total of nine circular ground plots were strategically positioned across the research site to provide comprehensive coverage. Within each ground plot, data collection followed a systematic approach. Information recorded for individual trees included species identification, azimuth (compass direction), distance from the center of the plot, tree status (e.g., live or dead), presence of any tree defects along with their type and position on the tree, degree of lean if applicable, DBH, and tree height. This detailed data collection process aimed to capture a comprehensive understanding of the forest ecosystem and facilitate accurate assessments of tree volumes and health.

Data analysis

Following data collection, all trees were aggregated. From here, defective trees were excluded from the final volume estimations, as defective trees would likely be ignored during harvest. Volume calculations were performed using a simplified approach, akin to calculating the volume of a cone. The formula employed for volume calculation is as follows:

$$Tree\ Volume\ (m3) = \frac{Tree\ Basal\ Area\ (m2) \times Tree\ Height\ (m)}{3}$$

RGB IMAGE ACQUISITION FROM RPAS AND PRE-PROCESSING

The study employed a RPAS, specifically a Mavic 2 Pro RPAS equipped with a high-resolution camera, to capture detailed imagery for survey purposes. Prior to conducting survey missions, preliminary steps were taken to ensure effective planning and execution. This included installing Map Pilot Lite for DJI from the App Store onto an iPad.

For mission planning, the survey area was identified considering relevant terrain and features. Mission planning was conducted using the Map Pilot's interface, resembling Google Earth. Boundary markers were placed on the interface to define the survey area, and flight altitude was adjusted to 80 meters to ensure detailed capture. The flight path direction was set according to the layout of the survey area, and the mission was saved for subsequent execution.

During flight execution, the planned mission was uploaded, and the programmed flight path was verified to ensure an 80% overlap. The flight was launched, with proper home point setup for automated return. The RPAS ascended and configured the gimbal for optimal image capture while navigating along the predetermined flight path, capturing images at specified intervals. Upon completing the survey mission, the RPAS returned to the home point for landing.

Following imagery collection, the data was transferred for processing. This involved transferring imagery to a USB drive for subsequent processing using a Maps Made Easy account. Imagery uploads and processing included selecting the appropriate workflow and providing project details. Processed imagery was verified for accuracy and processing times varied based on internet speed and file quantity.

Upon completion of processing, an email is sent containing links to the processed imagery and associated tools. Alternatively, processed imagery could be accessed by logging into the Maps Made Easy account, providing convenient access for analysis and further utilization. The Map Detail page provided comprehensive information about processed imagery, including timestamps, job details, pixel size, area coverage, and elevation range, facilitating detailed analysis and interpretation. Processed files, including GeoTIFF files, are downloadable from the Map Detail page, allowing integration with GIS systems and the creation of various mapping products.

The survey parameters included flying at a height of 80 meters with an 80% overlap to ensure comprehensive coverage and data accuracy. The data collected was subsequently analyzed using STEMS.

SINGLE TREE METRICS AND STAND ASSESSMENT (STEMS)

STEMS, is a RGB image based pre-harvest inventory tool that generates both spatial maps and aspatial summaries. This innovative tool boasts to estimate key tree parameters like geo-position, species, total tree height, basal area, volume, as well as aggregation summaries at various spatial units - like grid, stand, block. Leveraging this information alongside local allometric equations, STEMS is able to calculates the merchantable volume of a stand.

To effectively utilize STEMS, users must first ensure access to both RGB imagery and the corresponding point cloud data. Acquiring high-quality RGB imagery involves conducting an RPAS flights over the target forested area, while the generation of the point cloud necessitates software tools capable of processing this imagery suitable at producing precise 3D models. Once this data is obtained, users will need to have a client account with FPInnovations, the developer of STEMS. Account setup involves registering for a client account if not already done so and completing necessary authentication procedures.

Upon accessing their FPInnovations client account, users can navigate to the STEMS section within the platform. Here, they can upload the acquired RGB imagery and corresponding point cloud data following provided instructions. Within the STEMS interface, users integrate the uploaded data and initiate processing and analysis procedures guided by on-screen prompts and guidelines. Once processing is complete, users can access the generated volume estimates and analysis results provided by STEMS.

Under this study, all results were provided by FPInnovations, the developers of the STEMS model.

Harvesting process

The designated research block was subjected to a clearcut harvesting system. Under this method, the entire stand of trees within the block was harvested, leaving a minimum of 25 SPH, as required from the Ministry of Natural Resources (MNR). The harvesting process involved cutting the trees in a "cut-to-length" manner. This approach ensured that the harvested wood was processed into manageable log lengths at the stump, optimizing transport and handling.

Wood stacking and transport

Once felled and processed, the harvested wood was stacked at the roadside, strategically for ease of loading onto the log trucks. These log trucks were responsible for transporting the harvested wood to the designated mills for further processing (hardwood and softwood species were sent to different mills).

BILL OF LADING (BOL)

To ensure precise tracking and measurement of the harvested volume from the designated study block, a comprehensive BOL was meticulously prepared and assigned to each log truck. This document played a pivotal role in maintaining accurate records and facilitating data collection throughout the harvesting process.

Scale data collection

After all timber from the study block was delivered, each individual BOL issued to log truckers was systematically amalgamated into a Scaling Data System. This consolidation process encompassed all BOLs for both softwood and hardwood species from Romeo Mallette Block 483.

RESULTS

The total volume estimates obtained from various methodologies as seen in table 1 and figure 3, including FRI, ground survey, STEMS, and the final BOL data. Notably, the data reveal that STEMS provides the closest estimate to the BOL, with a total volume estimate of 10,354 m^3, closely aligning with the actual volume from the BOL, which stands at 9,747 m^3.

Table 1. Total volume estimates compared to the final BOL (m^3).

	Softwood	Hardwood	Totals
FRI	6,598.0	1,928.0	8,526.0
Ground Survey	10,122.0	655.0	10,777.0
STEMS	8,076.0	2,278.0	10,354.0
BOL	8,698.0	1,049.0	9,747.0

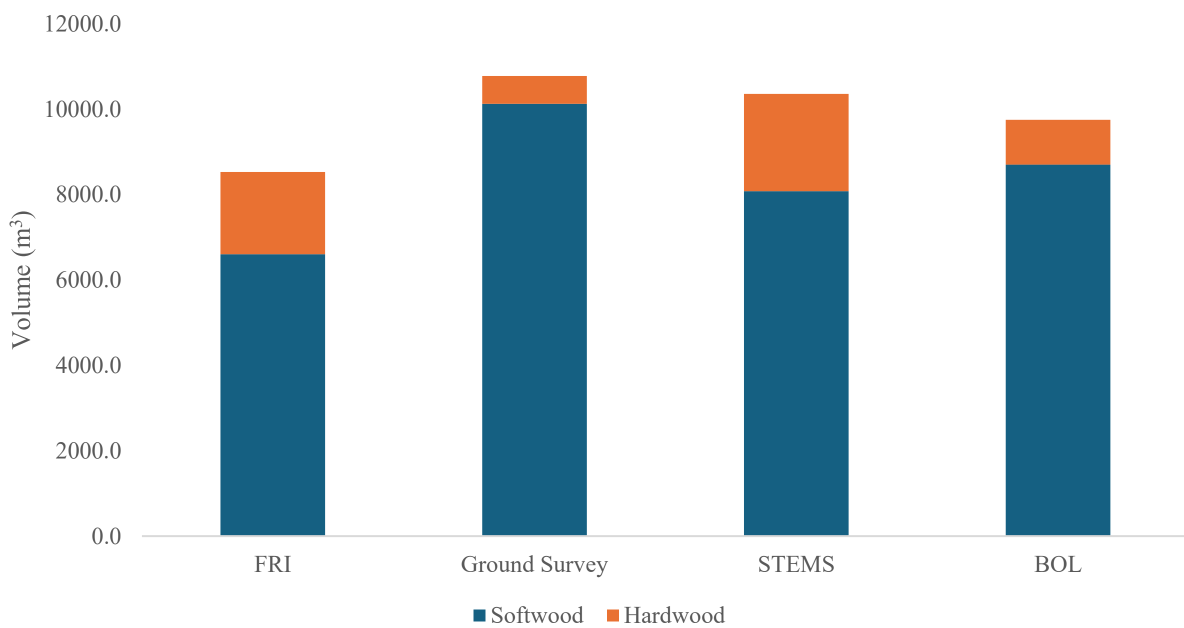

Figure 2. Total volume and species distribution (m^3).

The differences in total volume (m^3) compared to the BOL is outlined in table 6. Notably, STEMS demonstrates the smallest variation from the BOL, with a minor difference of 607 m^3. In contrast, the ground survey overestimated the total volume by 1,030 m^3, while FRI underestimated it by 1,221 m^3 relative to the BOL.

Table 2. Total volume difference from BOL(m^3).

	Softwood	Hardwood	Totals
FRI	-2,100.0	879.0	-1,221.0
Ground Survey	1,424.0	-394.0	1,030.0
STEMS	-622.0	1,229.0	607.0

Table 3 and figure 4 presents the volume per hectare (m^3/ha) derived from FRI, RPAS, ground survey, and STEMS, compared with the volume per hectare obtained from the BOL. The analysis reveals that both STEMS and the ground survey yielded the closest volume estimates, with 129.7 m^3/ha and 134.9 m^3/ha, respectively. These values closely approximate the volume per hectare indicated by the final BOL, which stands at 122 m^3/ha.

Table 3. Volumes per hectare compared to BOL (m^3/ha).

	Softwood	Hardwood	Totals
FRI	82.6	24.1	106.7
Ground Survey	126.7	8.2	134.9
STEMS	101.1	28.5	129.6
BOL	108.9	13.1	122.0

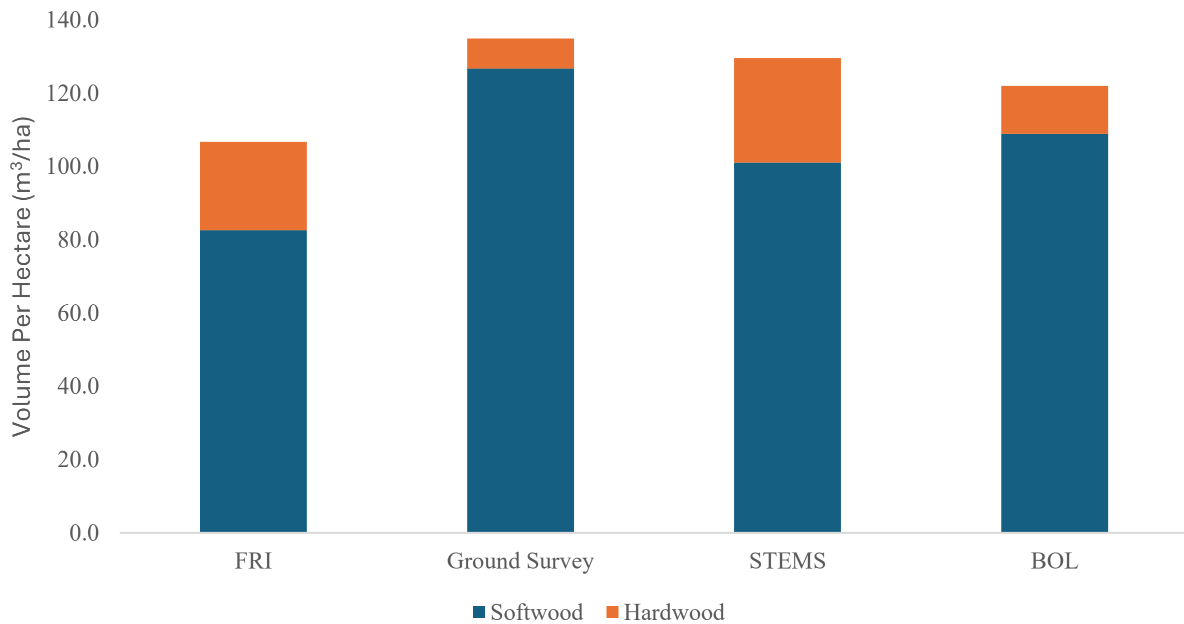

Figure 3. Volume per hectare by species (m^3).

The differences in volume per hectare (m³/ha) compared to the BOL can be seen in table 4. The data highlights that RPAS exhibited the largest disparity from the BOL, while STEMS demonstrated the smallest variation, differing by only 7.6 m³/ha. Additionally, the ground survey recorded a difference of 12.9 m³/ha, and FRI underestimated volume by 15.3 m³/ha relative to the BOL.

Table 4. Volume difference per hectare from BOL(m^3).

	Softwood	Hardwood	Totals
FRI	-26.3	11.0	-15.3
Ground Survey	17.8	-4.9	12.9
STEMS	-7.8	15.4	7.6

Table 5 illustrates the percent change from the BOL, offering insights into the magnitude of differences between various methods and the BOL. FRI underestimates by 12.5%. In contrast, the STEMS estimate demonstrates the smallest percent difference, with only a 6.2% difference from the BOL. With the ground survey presenting a 10.6% difference.

Table 5. Percent change from BOL (%).

	Softwood	Hardwood	Totals
FRI	-24.1	83.8	-12.5
Ground Survey	16.4	-37.6	10.6
STEMS	-7.2	117.2	6.2

DISCUSION

Total volume estimates compared to BOL

The comparison of total volume estimates from different methodologies, as shown in table 1, highlights significant variation in estimation accuracy. Surprisingly, STEMS provides the closest estimate to the BOL, with only a minor difference of 607 m^3 overall, representing a deviation of merely 6.2% from the actual volume. This finding aligns with previous research by White et al. (2014), which demonstrated the accuracy of remote sensing-based programs in volume estimations, particularly when compared to conventional ground surveys.

These results contradict my initial hypothesis, suggesting that ground surveys would provide the most accurate estimate, while STEMS would exhibit the greatest deviation. Furthermore, the literature review supports the idea that traditional methods, like ground surveys, often lead to biased estimations (Nakajima et al., 1996). While ground surveys offer valuable ground truthing, they may still overestimate or underestimate volume parameters due to inherent limitations in sampling intensity and coverage.

Volume per hectare compared to BOL

Table 2 provides a comparison of volume per hectare estimates. With STEMS showing closer alignment than ground surveys compared to the BOL in volume per hectare estimates, with differences of 7.6 m^3/ha and 12.9 m^3/ha, respectively. These deviations represent 6.2% and 10.6% from the BOL volume per hectare. These findings suggest the superior accuracy of remote sensing-based methods in capturing spatial variability within forest stands. This observation is consistent with the findings of Young et al. (2022), who also emphasized the achievable accuracy of remote sensing-based estimations. These results further contradict the hypothesis as the FRI data showed a 15.3 m^3/ha difference from the BOL, the largest deviation at 12.5%.

Volume difference from BOL

Figure 3 illustrates the differences in total volume estimates compared to the BOL across different methodologies. STEMS demonstrates the smallest variation from the BOL, with a difference of 607 m^3, representing a deviation of 6.2% from the BOL volume. In contrast, ground surveys tend to overestimate total volume by 1,030 m^3, corresponding to a deviation of 10.6% from the BOL volume. Conversely, FRI underestimates total volume by 1,221 m^3, indicating a deviation of 12.5% from the BOL volume. These findings are consistent with the literature review, which highlights the strengths and limitations of various estimation methods.

Volume difference per hectare from BOL

Figure 4 presents the differences in volume per hectare estimates compared to the BOL. FRI exhibits the highest deviation from the BOL, with an average difference of 15.3 m^3/ha, from the BOL volume per hectare. In contrast, STEMS demonstrates the smallest deviation, with an average difference of 7.6 m^3/ha, from the BOL volume per hectare. This remains consistent with

These outcomes align with findings from the literature review, which highlight the strengths and limitations of various estimation methods. Ground surveys offer valuable ground truthing but may suffer from biases in estimation accuracy (Nakajima et al., 1996). RPAS-based surveys, while providing accessibility and efficiency, may overestimate volume parameters related to broadleaved species due to challenges in capturing lower canopy levels (Young et al., 2022). Malta et al. (2023) presented a photogrammetry method, called Mask R-CNN model, which displayed similar levels of accuracy as STEMS at estimating tree biometric characteristics from photographs, offering another cost-effective alternative to traditional measurement methods.

CONCLUSION

In conclusion, this study aimed to assess the accuracy of various methods in estimating tree volumes in the Romeo Mallette Forest. Accurate volume estimates are crucial for effective forest management practices and decision-making processes. Contrary to our initial hypothesis, the results revealed that STEMS, a remote sensing-based method, provided the closest estimates to the BOL. This finding challenges the conventional belief that ground surveys would offer the most accurate estimates. Moreover, remote sensing-based methods, such as STEMS, demonstrated superior accuracy in capturing spatial variability within forest stands compared to ground surveys and FRI data.

Underscoring the importance of embracing technological advancements, particularly in remote sensing, to enhance the accuracy and efficiency of volume estimations in forestry operations. Furthermore, the study highlights the need for further research to explore the potential of emerging technologies and methodologies, such as photogrammetry, in improving volume estimation accuracy.

In conclusion, this study illuminates the intricate dance between technological advancements and forestry management, compelling foresters to conscientiously explore innovative avenues in their quest to harmonize resource utilization with environmental preservation.

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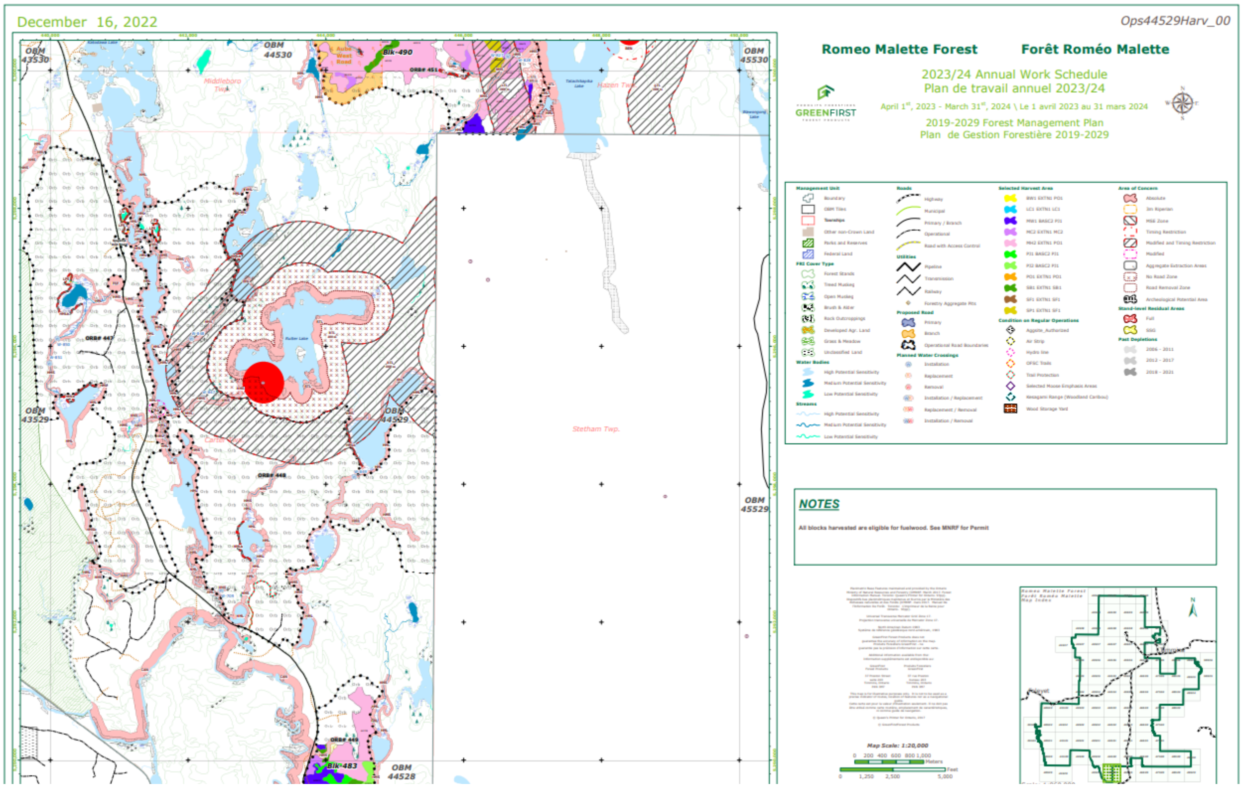
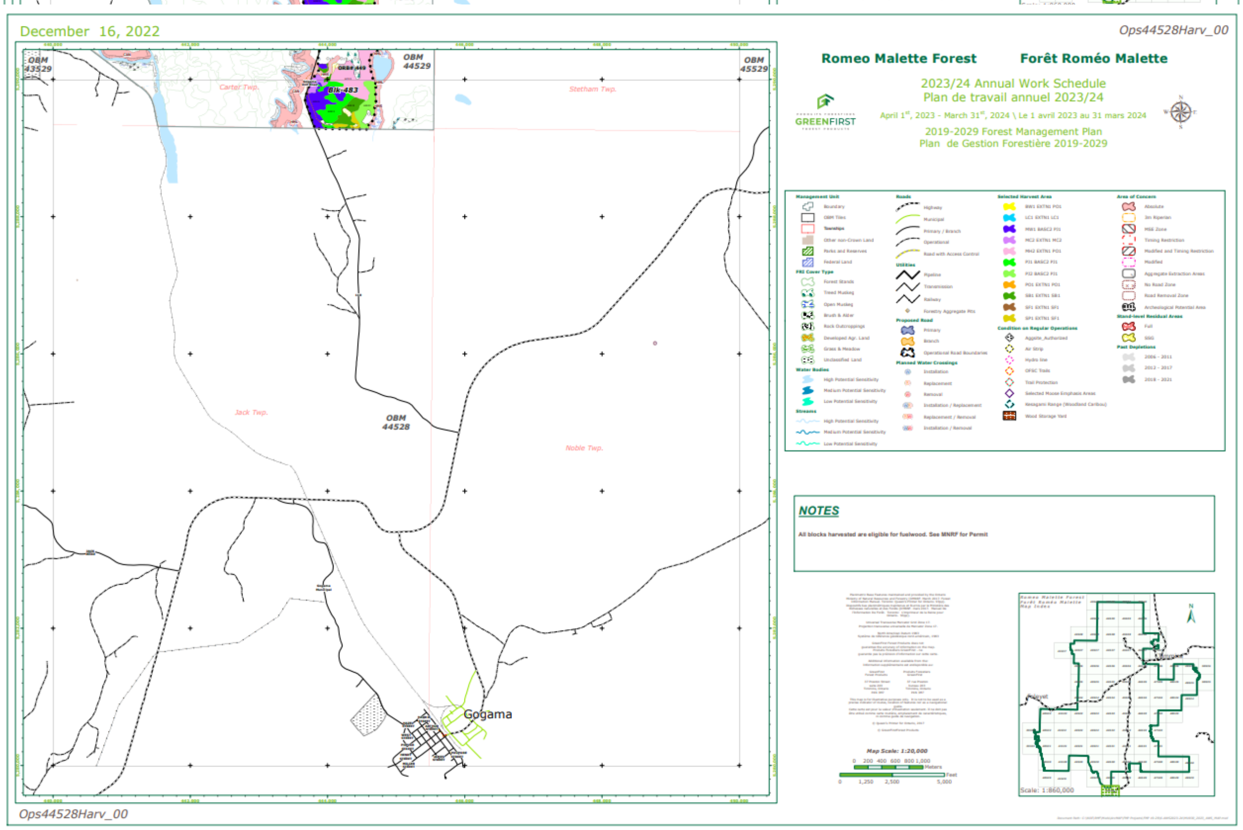
APPENDICIES





APPENDIX II

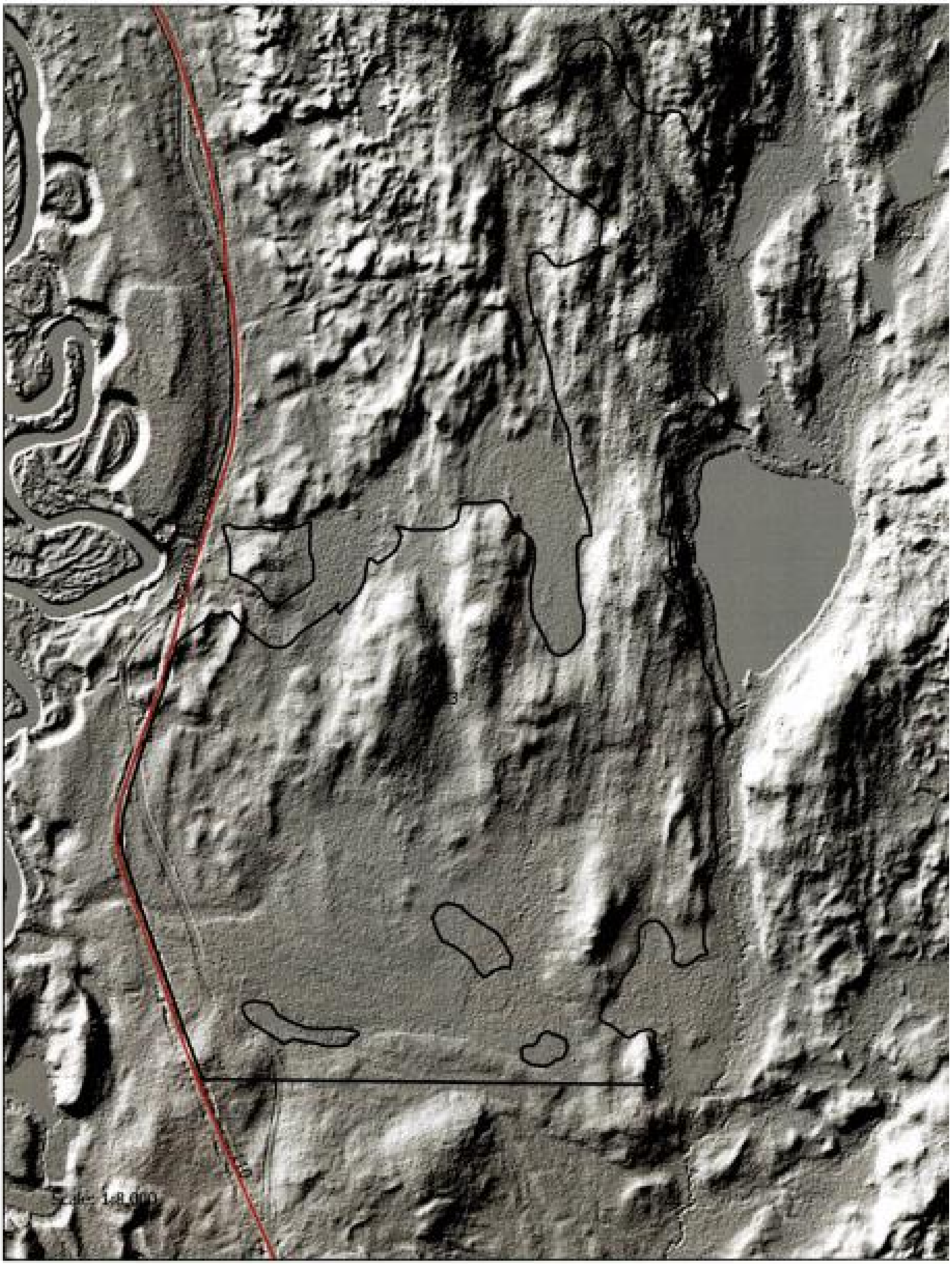
APPENDIX III

SPF BOLS

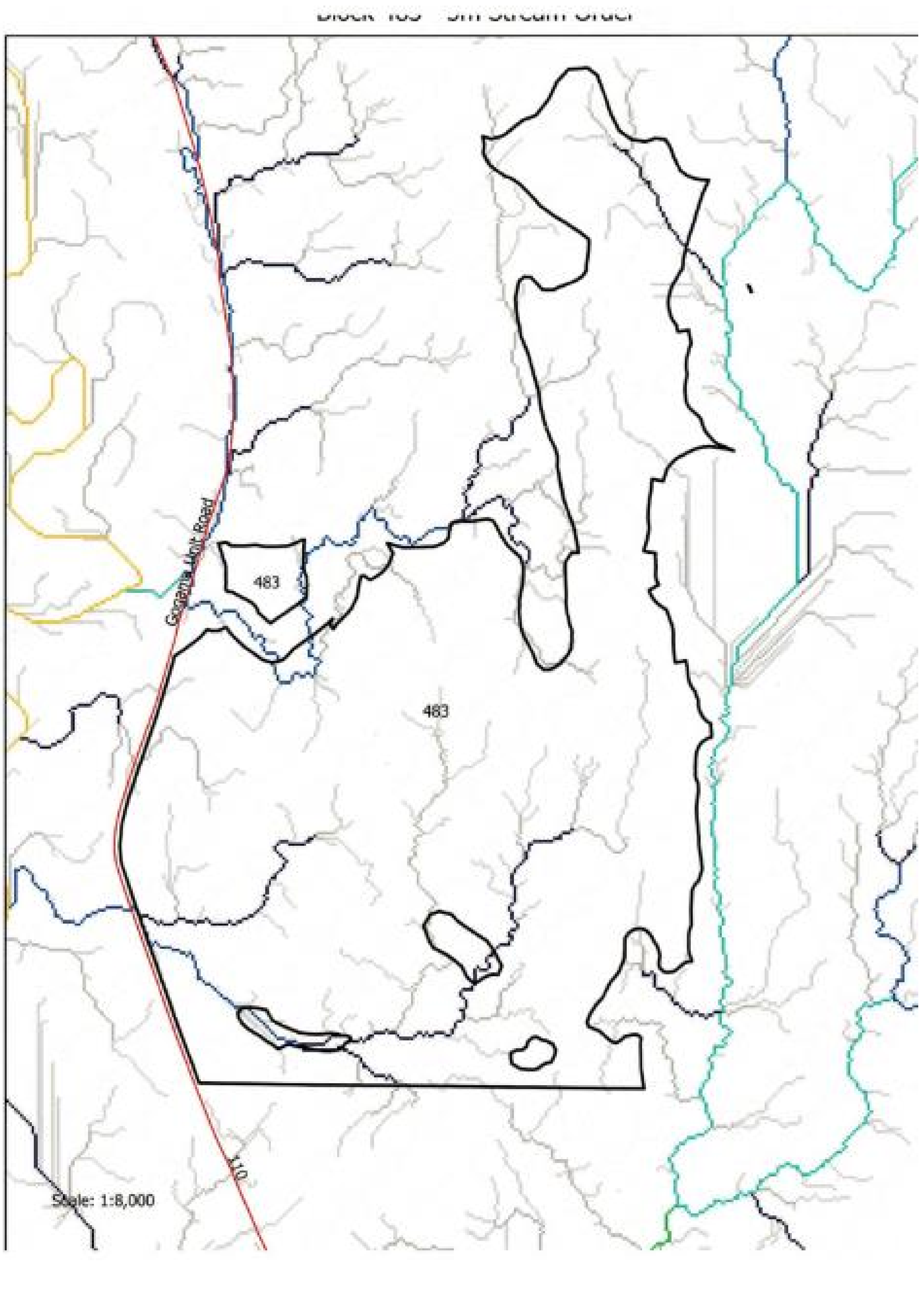
MILL	CONTRACTOR	PRODUCT	FMU	TICKET	BOL	DATE_IN	DATE_OUT	GROSS Kg	TARE Kg	NET Kg	GTV factor	GTV m3	GMV factor	GMV m3
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0313988	3416810	05-06-2023 14:00	05-06-2023 14:18	63620	19830	43790	837	52	840	52
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0314010	3416882	06-06-2023 08:03	06-06-2023 08:32	64230	21680	42550	837	51	840	51
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0315714	3416354	20-07-2023 06:58	20-07-2023 07:25	55760	19460	36300	772	47	772	47
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0315719	3416355	20-07-2023 07:40	20-07-2023 08:05	56070	19310	36760	772	48	772	48
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0315726	3416357	20-07-2023 09:01	20-07-2023 09:19	56410	19450	36960	772	48	772	48
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0315786	3416365	24-07-2023 08:01	24-07-2023 08:27	59970	21490	38480	772	50	772	50
OSTROM	PNG LOGGING	8 BALSAM FIR	930	OS0315808	3416369	24-07-2023 12:24	24-07-2023 12:47	58440	19080	39360	786	50	786	50
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0315814	3416371	24-07-2023 14:55	24-07-2023 15:18	57840	21310	36530	772	47	772	47
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0316516	3417224	15-08-2023 12:33	15-08-2023 12:58	54690	19140	35550	810	44	810	44
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0316782	3416325	23-08-2023 14:02	23-08-2023 14:14	39320	19270	20050	789	25	789	25
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0316894	3417096	28-08-2023 11:35	28-08-2023 11:55	56840	19250	37590	748	50	749	50
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0316963	3416502	29-08-2023 13:06	29-08-2023 13:33	58820	19520	39300	748	53	749	52
OSTROM	PNG LOGGING	8 BALSAM FIR	930	OS0316988	3416508	30-08-2023 06:30	30-08-2023 06:59	61620	19960	41660	829	50	829	50
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0519525	3416801	05-06-2023 12:36	05-06-2023 12:57	62950	22710	40240	817	49	817	49
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0519555	3416814	05-06-2023 18:02	05-06-2023 18:22	58660	19110	39550	817	48	817	48
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0519559	3416816	05-06-2023 18:25	05-06-2023 18:44	64970	19070	45900	817	56	817	56
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0519561	3416817	05-06-2023 18:38	05-06-2023 19:01	64030	19500	44530	817	54	817	54
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0519562	3416818	05-06-2023 18:47	05-06-2023 19:03	64100	19890	44210	817	54	817	54
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0519600	3416823	06-06-2023 08:36	06-06-2023 08:51	65180	20000	45180	817	55	817	55
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521504	3416353	20-07-2023 07:03	20-07-2023 07:18	63250	19590	43660	798	55	798	55
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521517	3416358	20-07-2023 11:00	20-07-2023 11:20	62100	19800	42300	798	53	798	53
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521518	3416359	20-07-2023 11:23	20-07-2023 11:38	63660	19450	44210	798	55	798	55
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521543	3416363	20-07-2023 18:18	20-07-2023 18:42	63020	19640	43380	798	54	798	54
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521723	3416335	26-07-2023 09:17	26-07-2023 09:33	63860	19080	44780	798	56	798	56
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521750	3416341	26-07-2023 15:43	26-07-2023 16:05	60820	21320	39500	798	49	798	49
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521823	3417206	27-07-2023 17:43	27-07-2023 18:03	64140	20600	43540	736	59	736	59
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521837	3417208	28-07-2023 05:42	28-07-2023 06:29	64530	19130	45400	736	62	736	62
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522277	3417211	14-08-2023 07:57	14-08-2023 08:30	64990	21710	43280	761	57	761	57
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522412	3416280	16-08-2023 06:12	16-08-2023 06:32	59380	18960	40420	761	53	761	53
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522430	3416282	16-08-2023 09:34	16-08-2023 09:52	59040	20210	38830	761	51	761	51
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522453	3416285	16-08-2023 13:58	16-08-2023 14:20	59860	20150	39710	761	52	761	52
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522466	3416288	16-08-2023 16:43	16-08-2023 16:55	57850	19950	37900	761	50	761	50
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522550	3416297	17-08-2023 16:17	17-08-2023 16:37	62160	19390	42770	759	56	759	56
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522764	3416323	23-08-2023 13:17	23-08-2023 13:33	64590	20020	44570	759	59	759	59
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522772	3417081	23-08-2023 15:01	23-08-2023 15:25	62660	21520	41140	759	54	759	54
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522774	3417082	23-08-2023 17:08	23-08-2023 17:25	63730	19920	43810	759	58	759	58
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522783	3417083	23-08-2023 18:17	23-08-2023 18:42	61490	19040	42450	759	56	759	56
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522811	3417086	24-08-2023 09:16	24-08-2023 09:30	58540	19690	38850	734	53	734	53
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522837	3417090	24-08-2023 17:36	24-08-2023 17:53	60490	19170	41320	734	56	734	56
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521646	3416326	25-07-2023 06:32	25-07-2023 06:48	60760	19610	41150	798	52	798	52
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521728	3416336	26-07-2023 10:51	26-07-2023 11:14	64410	19630	44780	798	56	798	56
TIMMINS	PNG LOGGING	CUT TO LENGTH BALSAM FIR	930	TI0521739	3416338	26-07-2023 12:24	26-07-2023 13:10	61130	20050	41080	812	51	814	50
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521747	3416340	26-07-2023 15:04	26-07-2023 15:22	62150	19510	42640	798	53	798	53
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521840	3417209	28-07-2023 09:57	28-07-2023 10:14	64580	19010	45570	736	62	736	62
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522272	3417210	14-08-2023 07:18	14-08-2023 07:44	64010	19350	44660	761	59	761	59
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522389	3416277	15-08-2023 16:11	15-08-2023 16:33	62270	19170	43100	761	57	761	57
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522393	3416278	15-08-2023 17:03	15-08-2023 17:33	61300	19020	42280	761	56	761	56
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522445	3416284	16-08-2023 12:59	16-08-2023 13:21	60110	20050	40060	761	53	761	53
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522672	3416310	22-08-2023 08:14	22-08-2023 08:27	60060	20080	39980	759	53	759	53
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522754	3416298	23-08-2023 09:33	23-08-2023 09:53	62680	19470	43210	759	57	759	57
TIMMINS	PNG LOGGING	CUT TO LENGTH BALSAM FIR	930	TI0522857	3417091	25-08-2023 07:04	25-08-2023 07:25	60670	19740	40930	845	48	846	48
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522861	3417092	25-08-2023 08:07	25-08-2023 08:31	62150	20080	42070	734	57	734	57
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0519584	3416878	06-06-2023 05:54	06-06-2023 06:09	60530	19350	41180	817	50	817	50
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0519589	3416879	06-06-2023 06:43	06-06-2023 07:01	63700	19460	44240	817	54	817	54
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0315793	3416366	24-07-2023 09:14	24-07-2023 09:47	60300	19150	41150	772	53	772	53
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0315812	3416370	24-07-2023 13:53	24-07-2023 14:15	54290	19430	34860	772	45	772	45
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0313979	3416802	05-06-2023 11:48	05-06-2023 12:56	63400	19740	43660	837	52	840	52
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0313996	3416819	05-06-2023 18:33	05-06-2023 18:57	61340	19050	42290	837	51	840	50
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0314025	3416883	06-06-2023 10:04	06-06-2023 10:33	62490	19210	43280	837	52	840	52
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0316714	3416312	22-08-2023 10:40	22-08-2023 10:56	58070	18940	39130	789	50	789	50
OSTROM	PNG LOGGING	8 CONIFER MIX	930	OS0316887	3417094	28-08-2023 09:28	28-08-2023 09:57	58400	19400	39000	748	52	749	52
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521677	3416330	25-07-2023 13:05	25-07-2023 13:24	64470	21660	42810	798	54	798	54
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0521814	3417204	27-07-2023 15:25	27-07-2023 15:43	63330	21600	41730	736	57	736	57
TIMMINS	PNG LOGGING	CUT TO LENGTH CONIFER MIX	930	TI0522362	3417219	15-08-2023 07:45	15-08-2023 08:07	61000	19350	41650	761	55	761	55

APPENDIX IV

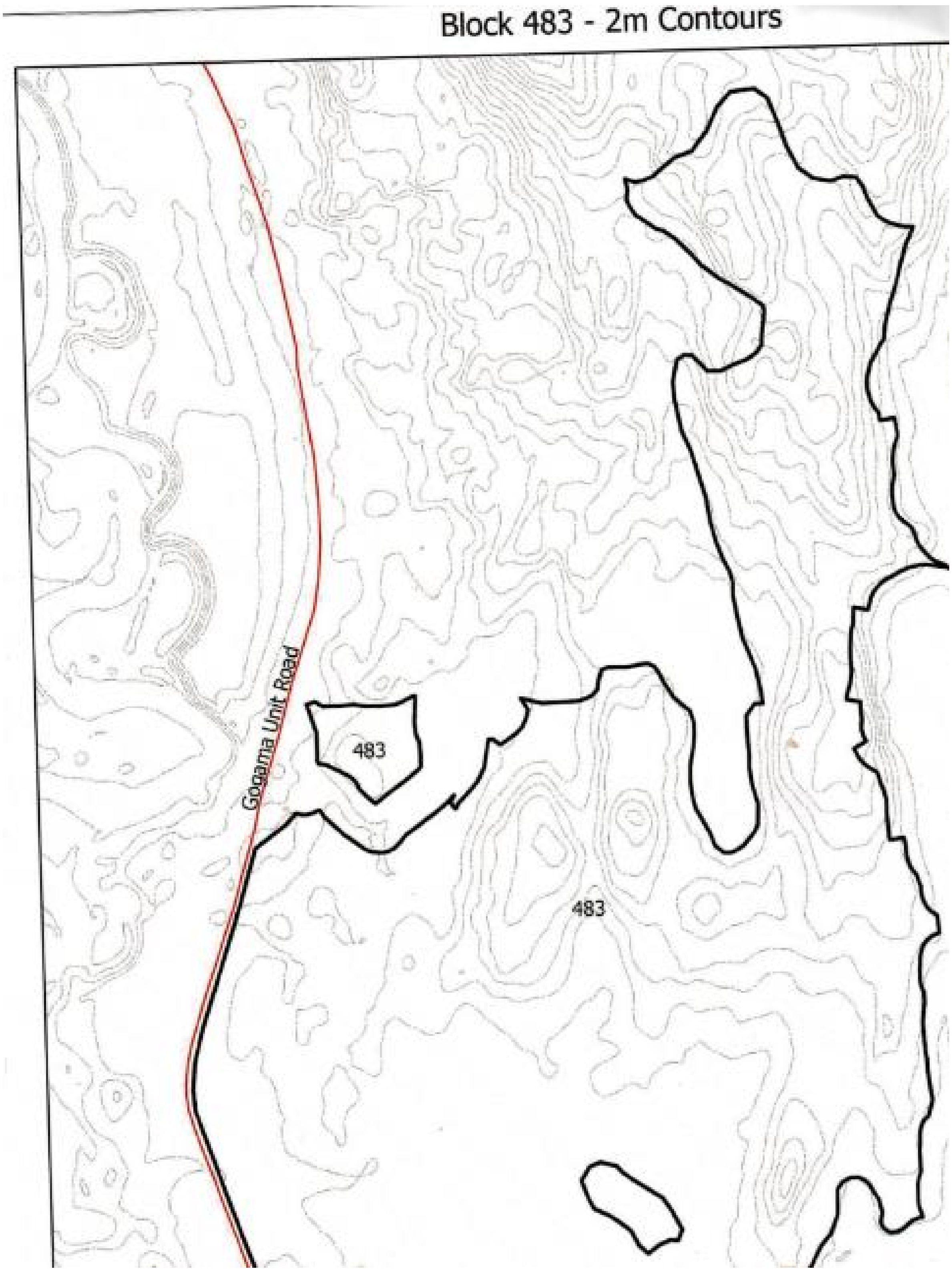
Block 483 - 2m Hillshade



APPENDIX V



APPENDIX VI



APPENDIX VII