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Use of geospatial technologies in New Zealand's plantation forestry sector – a decade of change

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Abstract

Background: Geospatial technologies have emerged as powerful tools for optimising forest management, improving operational precision, and supporting data-driven decision-making. This study aims to understand the technologies adopted by the New Zealand plantation forest industry and identify any barriers to the uptake of geospatial tools. This is the third such study, following comparable surveys in 2013 and 2018.

Methods: An online survey was sent to 29 organisations in New Zealand's forestry sector. Topics included organisation demographics, data acquisition, positioning technology, remote sensing technologies, software, and Artificial Intelligence (AI). Specifically, the survey focused on five remote sensing technologies: aerial photography, aerial videography, multispectral imagery, hyperspectral imagery, and LiDAR. Each section contained questions relating to the acquisition and application of the remote sensing technology and the software used for data processing. Questions were included to ascertain barriers to adoption. To identify changes in technology usage and uptake, results were compared to the 2013 and 2018 studies.

Results: Twenty-seven of the 29 queried organisations responded, resulting in a 93% response rate. Responding organisations managed 1,283,000 hectares (74% of New Zealand's plantation forest estate), with estate sizes ranging from about 7,000 to 200,000 hectares. Data acquisition from online portals included aerial imagery (100%), property ownership data (96%), and elevation data (89%), primarily from the Land Information New Zealand (LINZ) Data Service. Global Navigation Satellite Systems (GNSS) technology was universally employed. All respondents acquired aerial photography. In addition, 67% acquired multispectral imagery, 4% acquired hyperspectral imagery, and 93% acquired LiDAR data. The AI topic was surveyed for the first time and the technology was used by 30% of respondents when working with geospatial data. The main barrier to using remotely sensed data was the lack of perceived benefits, while the primary barrier to AI adoption was a lack of staff knowledge and training. Except for hyperspectral imagery, all remote sensing technologies saw increased uptake since 2013. LiDAR experienced the largest growth, with uptake increasing from 17% in 2013 to 93% in 2023. ArcGIS remains the primary tool for geospatial analysis, used by 96% of respondents. Notably, the use of open-source software such as QGIS increased by 31% over the past decade.

Conclusions: This study demonstrated an overall increase in the usage of geospatial technology in the forestry sector. To promote further uptake, it is important not only to increase exposure to available tools and provide training, particularly on emerging technologies such as AI, but also to demonstrate the practical and economic value these technologies can offer.

Keywords: Artificial intelligence; education; forestry; geospatial technologies; GIS; GNSS; GPS; remote sensing; UAV.

Introduction

Over the last decade, the New Zealand forestry industry has undergone significant transformations, including the adoption of geospatial technologies to support precision planning, operational efficiency and sustainable resource management (de Gouw et al. 2020; Morgenroth & Visser 2013). The rapid development of geospatial technologies over the past 50 years has made data acquisition and application in forest management more cost-effective and efficient (Lechner et al. 2020). These technologies, including Global Navigation Satellite Systems (GNSS), Geographic Information Systems (GIS), and remote sensing, provide accurate, site-specific data for decision-making and enable access to spatial information at unprecedented resolutions, such as wall-to-wall 3D datasets and sub-metre imagery.

The understanding and utilisation of geospatial technologies in forestry have grown significantly over time (Sonti 2015). While aerial photography has been employed for forest management since the 1940s (Standish 1945), the introduction and advancement of remote sensing technologies like Light Detection and Ranging (LiDAR), photogrammetry and positioning technologies has revolutionised precision forestry (Bill et al. 2022). Precision forestry involves using geospatial technologies and analytical tools to gather high resolution data tailored to specific forest management needs (Dash et al. 2016). These technologies have facilitated the creation of various products such as digital elevation models (DEMs), canopy height models (CHMs), and vegetation indices, which are invaluable for characterising forest resources and site conditions. The use of aerial videography is another tool used in forestry as unmanned aerial vehicles (UAVs) become more common among forestry organisations. Applications of aerial videography particularly include communication, mapping, and monitoring controlled burns (McElwee 2021).

Improved geospatial technologies and products have diverse applications across forestry operations, from forest boundary mapping (Xu et al. 2017), species classification (Deur et al. 2020), monitoring forest health (Housman et al. 2018), planning harvesting and road construction (González et al. 2008; Picchio et al. 2018), and conducting forest inventory (Lechner et al. 2020). By combining geospatial technologies with traditional ground-based methods, the accuracy and efficiency of forest descriptions, particularly for forest inventory, have improved (Pascual et al. 2020). Remote sensing data acquisition predominantly relies on satellites and aircraft (Fu et al. 2020). However, advancements in sensor technology and the emergence of UAVs have transformed geospatial data collection methods (Zhang & Zhu 2023), offering forest managers a timely, efficient, and cost-effective means of collecting data for specific target areas (Guimarães et al. 2020).

In New Zealand specifically, geospatial technologies have facilitated numerous improvements in plantation forestry. For instance, airborne LiDAR has been used for inventory (Watt et al. 2024) and harvest planning and road design (Dash et al. 2016). Additionally, multispectral satellite imagery has supported forest type differentiation (Xu et al. 2023), health assessments (Dash et al. 2018), and productivity analysis (Watt et al. 2016). The increased use of UAVs in New Zealand has further enabled plantation managers to rapidly acquire high-resolution imagery or LiDAR for estimating tree-level volume (Watt et al. 2025), biomass (Ye et al. 2025), and post-planting survival (Pearse et al. 2020).

An exciting next step in geospatial applications is the integration of Artificial Intelligence (AI), which refers to the development of computer systems that can mimic human intelligence, including learning from data, problem-solving, and understanding natural language. Subfields of AI include machine learning, deep learning, computer vision, and data analytics, enabling machines to perform tasks autonomously (Döllner 2020). In forestry, AI, specifically machine learning and deep learning, is transforming how forests are managed and monitored, enhancing decision-making processes and operational efficiency. For example, machine learning algorithms can analyse remote sensing data to automate forest inventory (Corte et al. 2020), identifying tree species (Deur et al. 2020) and estimating biomass and carbon storage (Fromm et al. 2019). Deep learning techniques, specifically convolutional neural networks (CNNs), are used for high-accuracy tree species classification (Egli & Höpke 2020), allowing managers to monitor biodiversity across large forest areas (Shivaprakash et al. 2022). In pest management, AI models can detect early signs of disease or pest infestation from high resolution imagery, helping to mitigate biosecurity threats before they become widespread (Liu et al. 2022). AI-based computer vision can identify seedlings from aerial imagery, enabling forest managers to assess reforestation progress without intensive ground surveys (Pearse et al. 2020). With continued advancements, AI-driven geospatial tools are expected to play an increasingly significant role in forest management, providing actionable insights that support sustainable forestry practices and improve the precision of operations.

However, there are ongoing challenges associated with the widespread use of geospatial technologies, particularly the shortage of skilled professionals. The role of spatial specialists, including GIS analysts, developers, and consultants, has been officially recognised on New Zealand's Long Term Skill Shortage List (LTSSL) (Land Information New Zealand 2025). This shortage can hinder the adoption of these technologies in various sectors, including forestry. Additionally, the cost of acquiring and utilising hardware and software for geospatial data processing can be a barrier for companies. Yet the availability of publicly accessible datasets and the existence of numerous software programmes, such as ESRI's ArcGIS, or free alternatives like QGIS and Google Earth, have made geospatial information more accessible and affordable. The increasing adoption of geospatial technologies in everyday forest management practices has made geospatial skills and knowledge essential for entry-level jobs in forestry companies (Bettinger & Merry 2018). Graduates in forestry are increasingly expected to have geospatial skills, reflecting the growing integration of geospatial components in forestry education programs (New Zealand School of Forestry 2023).

Previous studies that have investigated the uptake of geospatial technology identified the following barriers to the use of and entry to GIS: insufficient staff training programs, lack of awareness of tools and benefits, and lack of initiatives or mandates (Ye et al. 2013). In addition, lack of support from managers to understand technology, a shortage of technical capacity and trained personnel, a lack of financial capacity and a limited budget and, finally, an unwillingness to change (Kim et al. 2018).

Understanding the uptake, barriers and application of geospatial technologies in New Zealand's forest management sector holds significant importance. It enables organisations to optimise data utilisation and identify barriers, helping them develop strategies to overcome these barriers. This can lead to time and cost savings while providing new insights for decision-making. Two studies have been conducted on the uptake and barriers of geospatial technologies in this sector previously: a benchmark study in 2013 (Morgenroth & Visser 2013) and a follow-up survey in 2018 (De Gouw et al. 2020). We see an opportunity to update the available information on the adoption and application of these technologies in New Zealand's forest management sector, with the last study conducted five years ago.

Therefore, this study aims to address three main research objectives:

1. Identify current geospatial technologies employed in New Zealand's forest management sector.
2. Identify barriers hindering the adoption of geospatial technologies.
3. Determine changes in the uptake of geospatial technologies over the past ten years.

Methods

An online survey was developed and distributed to organisations in the forestry sector in August 2023 using Google Forms. This ensured that participants nationwide could conveniently and promptly receive and complete the survey. The survey was distributed to specific individuals or positions within each organisation. The initial list included organisations identified in the New Zealand plantation forest industry facts and figures publication (New Zealand Forest Owners Association 2023) that manage over 10,000 hectares. This ensures representation from organisations managing a significant portion of New Zealand's plantation forest estate. Additionally, other forestry organisations which are not included in this list but actively use geospatial technologies were also identified and considered. These particularly included forest consultants and research institutes.

All organisations were contacted before the survey was distributed to identify the best person within the organisation to complete the survey. The ideal respondent within each organisation was a GIS specialist who used the technology on a daily basis. This was to ensure all questions were understood, allowing for accurate representation of the organisation. Once the survey had been distributed, a 3-week period was given for respondents to complete the survey. A follow-up email was sent to non-respondents to encourage a higher response rate.

The survey questions were developed based on the previous studies conducted by Morgenroth and Visser (2013) and De Gouw et al. (2020), with necessary updates to reflect changes in available geospatial technologies. Each remote sensing technology had a definition associated with it to minimise confusion. The survey consisted of ten sections (the full survey can be found in the supplementary information) covering the following topics:

1. Respondent and organisation profile
2. Data acquisition
3. Positioning technology
4. Aerial photography
5. Aerial videography
6. Multispectral imagery
7. Hyperspectral imagery
8. LiDAR
9. Software applications used for geospatial data
10. Artificial Intelligence tools used for geospatial data

Due to the detailed nature of the survey, an estimated time of 30 minutes was required to complete the survey. An effort was made to provide multiple-choice questions, where expected answers had been generalised and provided for the respondent to select. Multiple-choice questions were accompanied by open-ended questions to allow respondents to provide additional details. Respondents also had the option to add answers not provided in the choices through an "other" option. Most questions were compulsory to ensure comprehensive responses.

The survey included conditional questions to tailor the survey flow based on respondents' previous answers. For example, if a respondent indicated the use of a particular remote sensing technology, subsequent questions would inquire about the data acquisition methods and the application of acquired products in forest management. If an organisation did not use a specific technology, questions would explore the reasons or barriers preventing its adoption.

The software application section of the survey included a table with each software used and the corresponding remote sensing data type or application. Respondents had the option to select which software is used for each remote sensing data type or application, providing an overview of software used within the industry. The layout for this question allowed respondents to complete the survey efficiently and ensure there were no repetitive questions for each remote sensing section, as the software used for each application might be similar. The final section on AI was a new addition to the survey series. It asked whether respondents had used AI for geospatial purposes and how they applied it.

To ensure the relevance and comprehensibility of the survey, a draft survey was administered to two industry experts, incorporating their feedback to make necessary revisions and additions. The final survey was then distributed to the selected organisations, and responses were recorded and analysed using descriptive statistics. Open-ended responses were categorised to identify trends and patterns. The full survey is provided as supplementary data.

Descriptive statistics were used to describe the current usage of geospatial technology and barriers associated with these technologies. Opened ended questions were grouped based on similarity to allow for trends to be identified. To determine the uptake and progression of the geospatial technologies, the survey results were compared to the findings of the previous study by Morgenroth and Visser (2013) and De Gouw et al. (2020).

Results and Discussion

Demographic information

Twenty-seven out of twenty-nine contacted organisations completed the survey, resulting in a 93% response rate. These organisations managed approximately 1,283,000 hectares of plantation forests, which accounts for 74% of New Zealand's 1.73 million hectares of plantation forest estate. The estates managed by individual organisations ranged from about 7,000 to 200,000 hectares. In terms of organisation types, 85% (n=23) were forest owners and/or managers, while 15% (n=4) were forest consultants or research institutes. The survey targeted each organisation's geospatial manager, but when unavailable, the most appropriate staff member responded. Among the respondents, most of them were in GIS-related positions, except 15% were foresters and 4% were wood-flow managers.

Data acquisition

All organisations used free, publicly available data portals to support forest management (Table 1). From these portals, aerial imagery was the most used product, with 100% of respondents employing it, followed by property ownership and boundaries (96%) and elevation data such as DEMs (89%). Other frequently accessed datasets were Land Cover Database (LCDB) (78%), hydrological features (67%), topographic maps (63%), roads and addresses (59%), the National Environmental Standards for Plantation Forestry (NES-PF) Erosion Susceptibility Classification (59%), and the digital soil map (S-MAP) (56%) were accessed by over 50% of respondents. Other datasets and online data portals were used by forestry organisations but had lower uptake.

Positioning technology

All organisations used GNSS technology, and 70% used two or more types of receivers, generally for different tasks. Consumer-grade receivers built into devices (e.g., smartphones) were the most widely used (81%), followed by consumer-grade handheld receivers (e.g., Garmin GPSMAP 62s) (70%). Survey-grade receivers, which offers sub-metre precision, were used by 37% of organisations. Mapping-grade receivers, which offer less than 5 m, were used by 26%. Two organisations (8%) used Satellite Based Augmentation Systems (e.g., SouthPAN) to improve GNSS precision and accuracy.

The primary applications of GNSS receivers were stand/forest mapping (such as locating planting extent) (48%), field navigation (44%), establishment of ground control points (30%), and hazard identification (15%). Other applications included forest inventory, road and cutover mark-ups (each used by 11% of respondents). Less common applications included historic or cultural site identification and species observation. Integrating GNSS technology with traditional ground-based methods significantly enhances the accuracy and efficiency of forest descriptions, such as those used in forest inventory (Pascual et al. 2020). This combined approach is likely to be highly beneficial for forestry organisations and could be further developed for improved forest management.

TABLE 1: Online data portal usage by respondents.

Portal	Usage (%)	Link
LINZ Data Service	100	https://data.linz.govt.nz/data/
Koordinates.com	81	https://koordinates.com/data/
Local Council	81	Various
Ministry for Primary Industries	59	https://data-mpi.opendata.arcgis.com/
Land Resource Information Systems Portal (LRIS)	56	https://lris.scinfo.org.nz/
Ministry for the Environment (MfE)	56	https://data.mfe.govt.nz/data/
National Institute of Water and Atmospheric Research[1] (NIWA)	30	https://data-niwa.opendata.arcgis.com/explore
Statistics New Zealand	15	https://datafinder.stats.govt.nz/

[1] Now Earth Sciences New Zealand

Remote sensing data

Aerial photography

Aerial photography was the most used data source by all respondents, with UAVs being the most common platform for acquiring it (93%), followed by aeroplanes (63%). UAVs provide timely, efficient and cost-effective data collection for specific target areas (Guimarães et al. 2020). Eleven percent of respondents acquired imagery via helicopter, and one respondent used Google Earth, a combination of aerial photography and satellite imagery. Ninety-six percent of respondents derived true-colour orthophotos, and 48% derived photogrammetric point clouds, primarily used for DEMs and stem counts.

The frequency of aerial photography acquisition was operation-specific, often coinciding with activities like pre- and post-harvest, post-planting, and cutover mapping. Estate-wide imagery was acquired at intervals ranging from monthly to every three years, depending on the data collection method and estate size. Spatial resolution varied based on the acquisition method and intended application. The spatial resolution of UAV-acquired imagery ranged from 0.02 m to 0.5 m, while airplane-acquired imagery ranged from 0.1 m to 0.5 m. Some organisations reported using resolutions of 2 m or larger, likely due to application needs or errors in responses.

Aerial videography

Fifty-six percent of respondents that responded to the survey acquired aerial videography. The main barrier to not using aerial videography was no perceived benefit (83%), and the current staff's lack of knowledge or training (42%). Cost (17%) and not aware of aerial videography (17%) were also barriers. For respondents who used aerial videography, they all acquired via UAVs (100%), and 20% also used helicopters to acquire aerial videography. Respondents only acquired aerial videography as required, mainly for environmental impact assessments such as assessing effects of windthrow.

Multispectral imagery

Multispectral imagery was acquired by 67% of respondents. The main barriers of using the imagery included no perceived benefits (56%), current lack of staff knowledge or training (44%) and cost (33%). Three respondents indicated they may use multispectral imagery in the future. Multispectral imagery was primarily acquired from satellites (89%), followed by aeroplanes (44%), and UAVs (22%). This aligns with findings from Fu et al. (2020) that multispectral imagery dominantly relies on satellites and aircraft. However, the increase in UAV data acquisition between 2018 and 2023, shows that advancements in sensor technology and the emergence of UAVs have brought about changes in geospatial data collection methods (Zhang & Zhu 2023).

The most common satellite sensors used by organisations included Sentinel-2 (87%), PlanetScope (53%), and Landsat (33%). Respondents derived various products from multispectral imagery, including true colour composites, false colour composites, and vegetation indices. The main vegetation index used was the Normalised Difference Vegetation Index (NDVI) (37%). Other less commonly used vegetation indices included Simple Ratio (SR), Enhanced Vegetation Index (EVI) and Soil Adjusted Vegetation Index (SAVI), each used by one respondent. The spatial resolutions of the multispectral imagery differed depending on the platform. The spatial resolution acquired using a UAV was 5 to 10 cm, aeroplane-acquired multispectral imagery had spatial resolutions ranging from 0.05 to 3 m, and satellite-acquired multispectral imagery ranged from 0.5 to 60 m.

Hyperspectral imagery

Only one respondent belonging to the respondent group - forest consultants or research institutes acquired hyperspectral imagery. The imagery was collected as needed, using UAVs or satellites. Barriers of not using the data included no perceived benefits (73%), current staff lack of knowledge or training (42%), cost (38%). While the use of hyperspectral data remains predominantly in the research domain, its utility for assessing disease (Watt et al. 2023), moisture stress (Watt et al. 2021), and nutrient status (Watt et al. 2020) has been demonstrated. However, its adoption in operational forestry remains limited, probably due to the high costs and complexity associated with data acquisition and processing.

LiDAR

LiDAR was used by 93% of organisations. All respondents managing 10,000 ha or more acquired LiDAR data. Of the two respondents not using LiDAR, both managed fewer than 10,000 ha forests. One cited a lack of perceived benefits as the main barrier, while the other mentioned that cost and current lack of staff knowledge or training as obstacles to using LiDAR.

When considering the acquisition and application of LiDAR data, there were notable differences between research institutes and consultancies, and forest management companies. Therefore, the following data analysis for LiDAR data was split into two categories: forest management companies and research institutes/consultancies.

Forest management companies mainly acquired LiDAR data via aeroplanes (67%) and open data portals (57%), followed by UAVs (29%) and satellites (10%). Point cloud densities acquired ranged from 1 to 25 points per square metre. Six companies collected LiDAR data for their entire forest estates once, with two continuing on a regular cycle of three to five years. Three companies did not know their point cloud density, and ten reported varying densities. Companies acquiring UAV LiDAR had point densities over 100 points per square metre. Seventy-six percent of forest management companies engaged third parties for data processing, while 24% processed in-house, mainly generating surfaces. The main applications of LiDAR-derived products included harvest planning (100%), road mapping (65%) and forest inventory (39%).

Research institutes and consultancies reported broader acquisition options, using open data portals (100%), UAVs (50%), airplanes (50%), static terrestrial platforms (50%), and mobile terrestrial platforms (50%). They collected LiDAR data as needed, with point densities ranging from 100 to 30,000 points per square metre. Seventy-five percent processed data in-house, focusing on a wide range of applications such as forest mapping, harvest planning, forest inventory, hazard assessment, survival analysis, and silvicultural planning.

Application of remotely sensed data

The most common applications of aerial imagery were cutover mapping, stand and forest mapping, and windthrow assessment (Table 2). Multispectral imagery was mainly used for cutover and forest stand mapping. LiDAR was primarily used for harvest planning, road mapping and forest inventory. LiDAR allows for rapid data collection over larger areas compared to time-consuming manual measurements. While LiDAR can be used to estimate individual tree heights (Zörner et al. 2018), most forestry organisations are using it for generating surfaces such as DEMs or CHMs, which are commonly used for mapping and forest inventory. Hyperspectral imagery had the lowest application rate, being used only for forest health assessment and species identification. Improved geospatial technologies and products are now applied across diverse forestry operations. Studies have shown that remote sensing is instrumental in forest mapping (Xu et al. 2017), species classification (Xu et al. 2023), monitoring forest health (Housman et al. 2018), identifying biosecurity threats (Dash et al. 2019), planning harvesting and road construction (González et al. 2008; Picchio et al. 2018), and conducting forest inventory (Lechner et al. 2020), aligning with the findings of this survey.

Software

Respondents primarily used ArcGIS Pro and ArcGIS Desktop to work with data collected from aerial photography, multispectral imagery, and hyperspectral imagery (Table 3). QGIS, a free open-source software, was also commonly used for aerial photography and multispectral imagery. ENVI was used for analysing hyperspectral imagery. For collecting and generating photogrammetric point clouds, the most common software included DroneDeploy (36%), Pix4Dmapper (36%), Agisoft Metashape (29%), and ESRI Drone2Map (14%). Other tools such as Site Scan, Maps Made Easy, and DJI Terra were each used by one organisation. The processing and analysis of photogrammetric and LiDAR point clouds were primarily done using Python and LASTools, respectively. Additionally, the open-source package LidR and related packages in R were commonly used (Table 4).

Artificial intelligence

As this was the first survey iteration to specifically include questions on AI use for geospatial purposes, we intentionally adopted a broad definition that includes

TABLE 2: Application of remote sensing imagery to forest management with the top five applications in each category shown in bold. The numbers represent the number of respondents.

Application	Aerial photography	Multispectral imagery	Hyperspectral imagery	LiDAR
Cutover mapping	**27**	**13**	0	6
Harvest planning	**27**	**13**	0	6
Stand/forest mapping	**26**	**13**	0	**12**
Windthrow assessment	**26**	**8**	0	6
Road mapping	**22**	3	0	**15**
Site preparation	21	2	0	9
Hydrological features	19	2	0	**12**
Silvicultural planning	19	3	0	9
Forest inventory	18	5	0	**13**
Hazards	16	0	0	9
Forest health assessment	15	**9**	**1**	4
Species identification	15	7	**1**	4
Fire assessment	13	1	0	3
Historic/cultural site identification	13	0	0	**11**
Landslide/soil displacement assessment	11	3	0	7

TABLE 3: Software used to visualise and analyse each type of imagery. The numbers represent the number of respondents.

Software class	Software	Aerial photography	Multispectral imagery	Hyperspectral imagery
Geographic Information system	ESRI ArcGIS Pro	24	16	0
	ESRI ArcGIS Desktop (e.g. ArcMap)	20	13	0
	QGIS (free)	10	6	0
	Google Earth Engine	4	4	0
	Global Mapper	2	1	0
	GRASS GIS (free)	1	1	0
Image analysis	ENVI	1	1	1
	ERDAS IMAGINE	0	0	0
	Trimble eCognition	0	0	0
Geospatial data programming	R (free)	4	4	0
	Python (free)	3	4	0
	GDAL (free)	2	2	0
Specialist forestry software	ATLAS GeoMaster	7	3	0

both classical machine learning algorithms (e.g., random forest) and more contemporary AI approaches, such as deep learning (e.g., CNNs). Future surveys will aim to refine this definition to provide clearer guidance for respondents and to enable more precise comparisons across different AI methodologies and stages of adoption and advancement.

Artificial intelligence was used by 30% of respondents when working with geospatial data. The main reasons that organisations had not adopted AI included lack of staff knowledge or training (68%), no perceived benefits (21%), lack of awareness of AI models (21%), and cost (11%). Two respondents indicated potential future use of AI. The most common AI models used were Random Forest (57%), CNN (57%), You only look once (YOLO) (29%), and eXtreme Gradient Boosting (XGBoost) (14%). These models were typically used in conjunction with remote sensing data, primarily from aerial photography (88%), followed by multispectral imagery (50%) and LiDAR (50%). Key applications of AI included stand/forest mapping (50%), forest inventory (50%), and tree detection (38%). Other applications were cutover mapping (25%), forest health assessment (25%), and silvicultural planning (25%). Less common uses included fire assessment, landslide or soil displacement assessment, species identification, and windthrow assessment, each by one respondent.

Artificial intelligence is still at an early stage of adoption in New Zealand's forest industry, but its integration with geospatial technologies presents a valuable opportunity to improve how plantation forests are managed. When applied effectively, AI can enhance decision-making by increasing operational efficiency, precision, and responsiveness. The adoption of AI in geospatial applications represents a major advancement in the sector (Shivaprakash et al. 2022) and is expected to grow (Chasmer et al. 2022). By combining machine learning, deep learning, computer vision, and data analytics, AI can support a wide range of decision-making tasks. Key applications include automated forest inventory (Hamedianfar et al. 2022), seedling identification (Fromm et al. 2019) and disease detection (Watt et al. 2024). Additionally, AI enables rapid analysis of large geospatial datasets from satellite imagery, UAVs, and ground-based sensors to provide timely insights

TABLE 4: Software used to process and analyse point clouds. The numbers represent the number of respondents.

Software	Photogrammetry point cloud	LiDAR point cloud
Cloudcompare	2	**3**
Computree	1	1
DJI Terra	1	1
Fusion	2	2
LASTools	2	**7**
LiDAR360	1	1
Python	**4**	**3**
R - LidR package	**3**	**4**
R - other packages	**3**	**3**

for forest management. For example, satellite-based machine learning approaches have effectively predicted disease outbreaks (Camarretta et al. 2024) and estimated forest carbon stocks (Illarionova et al. 2024), while UAV imagery combined with deep learning models has improved assessment of seedling detection (Pearse et al. 2020), forest health (Şandric et al. 2022) and fire detection (Shamta & Demir 2024). As AI capabilities expand, their integration with geospatial tools is expected to drive more proactive and data-informed approaches to plantation management.

Changes in uptake and barriers (2013-2023)

The uptake and barriers to using geospatial technologies have evolved over the past decade since the first (Morgenroth & Visser 2013) and second (De Gouw et al. 2020) comparable surveys. There have been changes in the proportions of organisations using each grade of GNSS receivers. In 2013, no companies reported using consumer-grade receivers built into devices such as mobile phones. This increased to 65% in 2018 and 70% in 2023 (Table 5). This rise is attributed to the availability, adaptability, accuracy, and low cost of smartphones (Zangenehnejad & Gao 2021). In contrast, the use of dedicated handheld consumer-grade devices (e.g., Garmin 60CSx) has decreased from 100% in 2013 to 83% in 2018, and further to 70% in 2023. The use of mapping-grade receivers decreased from 41% in 2013 to 22% in 2018 but increased slightly in 2023 to 26% of respondents. Survey-grade receivers are continuing to increase in usage, with 37% of respondents using these in 2023, an increase from 12% in 2013 and 22% in 2018. This increase is likely to relate to the increased use of remotely sensed data sets, particularly LiDAR data acquisition. The rise in the use of survey-grade receivers is likely due to the need to co-register LiDAR data and ground plots or to accurately map forest boundaries. Additionally, survey-grade receivers can offer enhanced accuracy under forest canopies compared with consumer-grade receivers (Danskin et al. 2009), which can be one of the most limiting factors for spatial positioning technologies when working in closed canopy forests.

The uptake of remote sensing technologies has generally increased over the past five and ten years, except for hyperspectral imagery (Table 6). Hyperspectral imagery usage decreased from 9% of organisations in 2018 to 4% in 2023. LiDAR demonstrated the most significant progression, with its uptake rising from 17% in 2013 and 70% in 2018 to 93% in 2023. Aerial photography maintained its universal usage, with 100% of companies using it both five years ago and now. The adoption of multispectral imagery showed a modest increase of 19%, rising from 48% to 67% use in the past five years.

The ubiquitous use of aerial photography highlights its importance in forestry management. While the derivation of true colour orthophotos has remained steady, the derivation of photogrammetric point clouds increased from 32% in 2018 to 48% in 2023. This rise is likely due to the lower costs associated with photogrammetric point clouds compared to LiDAR point clouds, despite their similar accuracies (Liu & Boehm 2015; Cao et al. 2019). A high-end photogrammetry system could cost up to USD 30,000 whereas manned LiDAR or UAV LiDAR systems can cost upwards of USD 150,000 and USD 120,000 respectively (Loosli 2023). Much cheaper consumer-grade UAV LiDAR systems, such as the DJI Zenmuse L1 and L2 sensors, cost around USD $8,000 and have proven effective in estimating DBH and volume (Watt et al. 2024), despite higher range measurement noise and positional errors compared with high-end LiDAR sensors (Mandlburger et al. 2023). Aerial videography, although not included in previous surveys, shows a high usage rate with 56% of respondents using it.

The uptake of multispectral imagery increased from 48% in 2018 to 67% in 2023. The spatial resolution of multispectral imagery now ranges more widely than in 2018, with UAV imagery achieving resolutions as fine as 5 cm and satellite-based products, particularly pan-sharpened products, reaching as fine as 50 cm. As sensors for multispectral imagery become more accessible and affordable for UAVs, its acquisition is likely to continue growing because of the information that can be gained due to increased spectral resolution. Studies have shown that infrared bands (when used in vegetation indices) can be used to support forest type differentiation (Ye et al. 2021), forest health assessment (Dash et al. 2018), biomass estimation (Naik et al. 2021).

The low uptake of hyperspectral imagery is expected due to the extensive data processing required for its high number of bands and the high acquisition costs (Hycza et al. 2018). Current applications of hyperspectral imagery are primarily in the research phase, focusing on forest species identification (Modzelewska et al. 2020), nutritional deficiency detection (Watt et al. 2019) and moisture stress assessment (Watt et al. 2021). Photogrammetric processing and multispectral imagery have proven to be viable alternatives for these applications (Guimarães et al. 2020), further limiting the utility of hyperspectral imagery. The most reported barrier to adopting hyperspectral imagery was a perceived lack of benefits, suggesting that users have yet to see compelling value in operational contexts. Despite the gradual reduction in hyperspectral imagery costs (Hycza et al. 2018), acquisition remains expensive due to the limited number of providers in New Zealand (Schimel 2020). However, as hyperspectral data becomes

TABLE 5: Comparison of percentage of respondents using GNSS receivers by grade in 2013, 2018 and 2023.

Year	Consumer - built into device	Consumer - handheld	Mapping	Survey
2013	-	100	41	12
2018	65	83	22	22
2023	81	70	26	37

TABLE 6: Comparison of percentage of respondents using remotely sensed imagery in 2013, 2018 and 2023.

Year	Aerial photography	Aerial videography	Multispectral imagery	Hyperspectral imagery	LiDAR data
2013	88	-	35	-	17
2018	100	-	48	9	70
2023	100	56	67	4	93

more affordable and demonstrates clear benefits for forest management over other remote sensing methods, its adoption may increase in the future.

The uptake of LiDAR has seen the most significant increase over the past 10 years, with all organisations managing more than 10,000 hectares now using this data. One of the biggest changes in LiDAR data acquisition between 2018 and 2023 was the introduction of open data portals. These portals have become one of the most common ways respondents acquire LiDAR data. The National Elevation Programme, which aims to provide LiDAR coverage across approximately 80% of the country (Land Information New Zealand 2023a), has contributed to the availability of freely accessible LiDAR data in New Zealand. Whilst this data is still limited to some parts of New Zealand, it covers a significant portion of New Zealand's plantation forests. This accessibility has created opportunities for smaller organisations that were previously restricted by the cost of acquiring LiDAR data. Furthermore, the availability of ready-to-use products derived from LiDAR data, such as DEMs and Digital Surface Models (DSMs), has benefited forest managers who previously lacked the expertise or resources to process LiDAR data themselves. In addition to improved accessibility, the growing adoption of LiDAR is likely driven by its widely recognised value in operational forestry. Enhanced inventory accuracy can help reduce harvesting costs and increase buyer confidence, hence contributing to higher returns from forest sales. This compelling value proposition, reinforced by frequent exposure at industry forums and events, has further supported its uptake. Both the 2013 and 2018 surveys suggested that cost was the largest barrier to acquiring LiDAR data, but the 2023 survey indicates that cost is now as much a barrier as staff training and lack of perceived benefits. As more LiDAR data becomes openly available, its usage is expected to increase. However, the forestry industry may face challenges in adoption due to a shortage of trained GIS specialists, which are listed on New Zealand's "Long term skill shortage list" (Land Information New Zealand 2025).

This survey also looked at forest research institutes and companies separately for the first time, with results indicating research institutes appear significantly more advanced in LiDAR acquisition than forest companies. Static and mobile terrestrial platforms were only used by two companies, likely due to their lack of suitability for large-scale forests (Chen et al. 2019). Most companies that process their own LiDAR data use a limited number of processing methods, primarily focusing on generating surfaces. In contrast, research institutes undertake detailed processing of point clouds and work with cutting-edge technologies such as deep learning fulfilling their role of testing and de-risking technologies to pave the way for adoption by companies.

The increasing use of AI in society is reflected in its growing use by a notable portion of forestry organisations, likely driven by advancements in computing power and AI algorithms. However, the most common barrier preventing AI usage was the lack of staff knowledge and training. More education and training for geospatial professionals will be required to understand and utilise AI models. Tertiary education and training providers will likely have the most impact on the future uptake of AI models. AI models were most commonly used in conjunction with high-resolution aerial photography, highlighting the ongoing importance of aerial photography in the forestry industry.

The most frequently cited barrier to adopting geospatial technology was a limited perception of its benefits. This marks a shift from previous studies, where barriers were more often related to staff education and the cost of data acquisition. This shift could indicate an increase in skilled GIS analysts entering the workforce, potentially influenced by the undergraduate and postgraduate geospatial courses taught at 12 tertiary institutes around New Zealand (Land Information New Zealand 2023b), and over 50% of young geospatial professionals holding postgraduate degrees (De Róiste 2016). It may also reflect that some users have trialled geospatial technologies in the past but did not see sufficient value for their specific operational context. In such cases, the barrier may come from experience rather than a lack of awareness, which suggests a need to better demonstrate the tangible benefits of these technologies. More broadly, this shift in barriers could signal that the sector is entering a new phase of the technology adoption cycle. With most foundational tools now in routine use and the 'low-hanging fruit' largely addressed, future growth may depend on developing new, value-adding applications, particularly those powered by AI. Demonstrating their utility in forestry settings and building practitioner capability will be essential to driving the next wave of innovation and uptake.

The survey results indicate significant changes in the uptake of software used for processing and using products from geospatial technologies in New Zealand's plantation forest management sector over the past five and ten years (Table 7). The largest increase was in the uptake of free GIS software, which grew from 6% in 2013 to 22% in 2018 and then to 37% in 2023. ERSI ArcGIS has experienced a notable increase in use, rising by 14% compared to 2013. In contrast, the use of MapInfo dropped from 18% in 2013 to 0% in 2018, and it has continued to have no usage within the industry in 2023. In terms of commercial image analysis software, ERDAS and Trimble e-Cognition both showed decreases of 13% and 4%, respectively between 2018 and 2023. There was a significant increase in organisations using point cloud analysis and processing software in 2023, with use of LAStools increasing by 26% since 2013. This growth in LiDAR processing tools aligns with the increased LiDAR acquisitions reported in the survey.

Future survey considerations

This study focused on the uptake of geospatial technologies but did not assess the value realised from their use. Future surveys should address this by including questions on perceived benefits, cost-effectiveness, and return on investment, and by analysing how these outcomes vary across different estate sizes and ownership models.

Additionally, this survey used a deliberately broad definition of AI, including both classical machine learning methods and more recent deep learning techniques. While this approach provided an initial overview of tools currently in use, it limits the ability to track the uptake of emerging AI technologies. Future surveys will adopt a more refined definition that emphasises contemporary deep learning and computer vision methods to enable clearer analysis of adoption trends.

Although this survey primarily targeted organisations managing large forest estates, future iterations should also consider placing emphasis on organisations with smaller holdings, which may play a role in driving innovation and early adoption of emerging technologies.

Conclusions

The survey provides insights into the uptake and barriers of geospatial technologies use in the New Zealand plantation forest management sector. The survey included responses from 27 organisations, showing a high use of online data portals and freely available datasets. GNSS receivers and aerial photography were the most common geospatial technologies, used by all respondents. Aerial videography, multispectral imagery, and LiDAR were also used by most respondents. Although AI has been used by a few respondents, there is potential for increased use in the future. Hyperspectral imagery, on the other hand, has seen a decrease in usage.

The most common barriers restricting the use of geospatial technologies were no perceived benefits.

TABLE 7: Progression of uptake of software used when processing and using products from the geospatial technologies included in the survey. - means the tool was not reported in the response.

Software class	Software	Organisations using software (%)				
		2013	2018	2023	10-yr change	5-yr change
Geographic Information Systems	ESRI ArcGIS (Desktop and Pro)	82	91	96	+14	+5
	MapInfo	18	0	0	-18	+0
	Global Mapper	0	9	7	+7	-2
	Free GIS (QGIS, GRASS GIS)	6	22	37	+31	+15
Image Analysis	ERDAS IMAGINE	12	13	0	-12	-13
	Trimble eCognition	0	4	0	+0	-4
	ENVI	-	-	4	N/A	N/A
	Google Earth Engine	-	-	19	N/A	N/A
Geospatial programming	GDAL*	-	-	7	N/A	N/A
	Python	-	-	15	N/A	N/A
	R (LidR or other)	-	-	15	N/A	N/A
LiDAR or photogrammetric point cloud analysis and processing cloud analysis and processing	FUSION	0	9	7	+7	-2
	LAStools	0	9	26	+26	+17
	QT Modeller	0	9	0	+0	-9
	Agisoft Metashape	0	9	15	+15	+6
	Cloudcompare	-	-	11	N/A	N/A
	Computree	-	-	4	N/A	N/A
	DJI Terra	-	-	4	N/A	N/A
	LiDAR360	-	-	4	N/A	N/A
Specialist forestry software	ATLAS GeoMaster	35	43	26	-9	-17

**While only a few respondents explicitly reported using GDAL (Geospatial Data Abstraction Library), its actual use is likely more widespread as GDAL serves as a core dependency for many geospatial libraries in Python and R.*

Compared to barriers identified in previous surveys by De Gouw et al. (2020), staff knowledge and skills, and the cost of acquiring data is becoming less of a barrier. In 2018, cost was the main barrier for organisations not using LiDAR. The increasing availability and use of free online data portals and datasets, such as LiDAR from the NZ National Elevation Programme, may have impacted these barriers. The uptake of AI was primarily limited by a lack of staff training, indicating the need for further education in this area of geospatial technology.

The results of this survey highlight the continuing use and growing importance of geospatial technology in the forest management industry. These findings will help inform the industry on how to better capitalise on their acquired data and develop strategies to overcome identified barriers, ultimately promoting the widespread use of geospatial technology. While improving access and training, particularly for emerging technologies such as AI is important, it is equally important to demonstrate the practical and economic value these tools can deliver. A clearer understanding of such benefits is likely to support broader uptake across the sector. As access improves and applications mature, geospatial technologies are expected to play an increasingly integral role in forest management.

Competing interests

The authors declare that they have no competing interests.

Author contributions

CX: supervision, survey design, manuscript writing and editing. AM: survey distribution, data analysis, manuscript writing. NY: supervision, survey design, manuscript editing. JM: study conception, supervision, survey design, manuscript editing.

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Supplementary Information

Survey Details

Introduction

You are being invited to participate in a research project concerning geospatial technologies used in the New Zealand Forest Industry. This is being conducted by a final-year student from the School of Forestry, University of Canterbury, undertaking a Bachelor of Forest Engineering with Honours. This is the third time that the School of Forestry has run this survey, with previous surveys having been sent to industry in 2013 (Morgenroth & Visser 2013) and 2018 (de Gouw et al. 2020).

The intended recipient of this survey is your company's geospatial manager or a person with knowledge of your company's use of geospatial data, methods, software, and hardware. Before you decide to take part or not, it is important to understand the rationale for the research, and what participation involves.

Please read the following information. Feel free to discuss this with others, or ask for any clarification from the research team, and take time to decide whether to take part or not.

Why is this research being conducted?

The aim of this project is to understand the uptake of geospatial technologies in the New Zealand forestry industry. Specifically, the project seeks to understand which technologies have been adopted by the New Zealand Forest industry and to identify any barriers to the uptake of geospatial tools. It is hoped that this will help inform the industry on how to fully capitalise on their acquired data, as well as develop strategies to overcome any barriers identified, ultimately promoting widespread use in the industry.

Do I have to participate?

Participation is voluntary. In 2012, 17 companies participated, while in 2018, 23 companies participated. If you do not wish to participate or wish to withdraw from the questionnaire after starting it, please close your web browser, as incomplete questionnaires will be discarded. Doing so does not require a reason and has no consequences.

What will happen if I choose to take part?

If you do choose to participate, you will be invited to complete an online questionnaire, that will take approximately 30 minutes to complete. We may contact you to clarify your responses, if necessary.

What are the advantages of taking part?

There are no immediate benefits, financial incentives, rewards, or otherwise for participating in this research. However, it is hoped that this research project will help inform the industry on the current uptake of geospatial technologies and contribute to maximising the efficiency and effectiveness of forest management practices in New Zealand. Importantly, it helps to ensure that the geospatial curriculum at the School of Forestry continues to meet industry's needs by identifying commonly used data, methods, software, and hardware.

What are the possible disadvantages of taking part?

The research team anticipates no significant disadvantages associated with participation.

If I choose to take part, what will happen to the data?

The results of this survey will be used in comparison with the previous surveys completed in 2012 and 2018 to identify how the use of geospatial technologies has changed. All responses to the survey will be aggregated such that no individual company's geospatial strategy is detailed or compromised. The use of this data will be limited to addressing the research purpose.

At the end of this research project, a publicly available dissertation, including summaries of the anonymised data will be written. In addition, the research team may write and publish a journal article. In either case no information identifying participants or companies will be accessible. Examples of how the previous survey data were used can be found in Morgenroth & Visser (2013) and de Gouw et al. (2020).

Contact Details

If you would like more information, or have any questions about the project or your participation, please use the contact details below:

Primary contact

Name: Anna Manning
Role: BE(Hons) Forest Engineering Final Year Student
Email: ama557@uclive.ac.nz

Supervisor

Name: Dr Vega Xu
Role: Dissertation supervisor
Email: cong.xu@canterbury.ac.nz

If you have concerns about any aspect of this research project please contact Anna Manning in the first instance, then escalate to Vega Xu, the Supervisor.

We are particularly interested in gathering information relevant to the present. Please answer the following questions based on your company's current geospatial technology usage.
* Required

Company Profile

1. What is your name? *
2. What is your position title? *
3. What is the name of your company? *
4. Type of company? *
    a. Forest Owner and Manager
    b. Forest Manager
    c. Forest Consultant
    d. Other (please specify):
5. What is the net stocked area (hectares) of forests that your company manages in New Zealand? *
6. What stand record system do you use? (e.g. Geomaster)
7. What forest estate model do you use? (e.g. Woodstock or Tigermoth)

Public Data Acquisition

8. Does your company use the Land Information New Zealand (LINZ) geographic data portal? *
    a. Yes
    b. No
9. Which of the following datasets does your company use from the Land Information New Zealand (LINZ) data portal?
    a. Aerial photography
    b. Elevation (e.g. Digital Elevation Models)
    c. Property Ownership & Boundaries
    d. Roads and Addresses
    e. Topographic maps
    f. Hydrological features (e.g. rivers, wetlands)
    g. Other (please specify):
10. Does your company use the Koordinates geographic data portal? *
    a. Yes
    b. No
11. Which of the following datasets does your company use from the Koordinates data portal?
    a. Virtual climate station network from NIWA
    b. Aerial photography
    c. Elevation (e.g. Digital Elevation Models)
    d. Property Ownership & Boundaries
    e. Roads and Addresses
    f. Topographic maps
    g. Hydrological features (e.g. rivers, wetlands)
    h. Land Cover Database (LCDB)
    i. New Zealand Environmental Data Stack (e.g. soil particle size, slope, annual precipitation)
    j. The digital soil map (S-MAP)
    k. Fundamental Soils Layer (FSL) (e.g. Soil Drainage)
    l. Territorial Authority Boundaries
    m. Statistical Area Boundaries
    n. Land Use Carbon Analysis System (LUCAS)
    o. Land Environments New Zealand (LENZ)
    p. Climate (e.g. annual rainfall)
    q. Scion's Geospatial Surfaces (e.g. Site productivity layers)
    r. Other (please specify):
12. Does your company use the Land Resource Information Systems (LRIS) geographic data portal? *
    a. Yes
    b. No
13. Which of the following datasets does your company use from the Land Resource Information Systems (LRIS) data portal?
    a. Land Cover Database (LCDB)
    b. New Zealand Environmental Data Stack (e.g. soil particle size, slope, annual precipitation)
    c. The digital soil map (S-MAP)
    d. Fundamental Soils Layer (FSL) (e.g. Soil Drainage)
    e. Elevation (e.g. Digital Elevation Models)

    f. Land Environments New Zealand (LENZ)
    g. Other (please specify):

14. Does your company use the Ministry for the Environment (MFE) geographic data portal? *
    a. Yes
    b. No
15. Which of the following datasets does your company use from the Ministry for the Environment (MfE) data portal?
    a. Land Use Carbon Analysis System (LUCAS) Land Use Map
    b. Land Use Carbon Analysis System (LUCAS) NZ Forest Clearing 2008-2020
    c. Climate (e.g. annual rainfall)
    d. Hydrological features (e.g. rivers, wetlands)
    e. Other (please specify):
16. Does your company use the Stats NZ data portal? *
    a. Yes
    b. No
17. Which of the following datasets does your company use from the Stats NZ data portal?
    a. Territorial Authority Boundaries
    b. Statistical Area Boundaries
    c. Other (please specify):
18. Does your company use Council geographic data portals? *
    a. Yes
    b. No
19. Which of the following datasets does your company use from the Council's data portals?
    a. Property Boundaries
    b. Aerial Photography
    c. Other (please specify):
20. Does your company use any other geographic data portals?
    a. No
    b. MPI data portal – NES-PF Erosion Susceptibility Classification
    c. NIWA - Virtual climate station network
    d. Other (please specify):

Positioning Technology

Positioning technology is the use of a global navigation satellite system (GNSS) to provide positioning, navigation, and timing data, this includes GPS, Galileo, GLONASS and BeiDou.

21. What grade of global navigation satellite system (GNSS) does your company use? *
    a. Consumer grade receiver built into device (e.g. iphone)- capable of <10m accuracy
    b. Consumer grade receiver (e.g. Garmin GPSMAP 62s)- capable of <10 m accuracy, cost <$1,000
    c. Mapping grade receiver (e.g. Trimble Nomad)- capable of <5 m accuracy, cost $1,000-$5,000
    d. Survey grade receiver (e.g. Trimble GeoExplorer)- capable of <0.5 m accuracy, cost $5,000 +
    e. None
22. Does your company use Satellite Based Augmentation Systems (e.g. SouthPAN)- capable of <0.1 m accuracy?
    a. Yes
    b. No
23. How does your company use its GNSS receiver(s)? * (e.g. boundary mapping)

Aerial Photography

Aerial photography consists of three bands (red, green, blue) and is acquired from an aerial platform. (e.g. plane, UAV).

24. Does your company use aerial photography? *
    a. Yes
    b. No
25. What are the reasons for not using aerial photography? *
    a. Cost
    b. No perceived benefits
    c. Current staff lack of knowledge or training to use aerial photography
    d. Was not aware of aerial photography
    e. Other (please specify):
26. How is your aerial photography acquired? *
    a. Unmanned Aerial Vehicle (drone)
    b. Airplane
    c. Helicopter
    d. Other (please specify):
27. Do you derive true colour orthophotos (contain only red, green and blue bands (RGB)) and are geometrically corrected) from aerial photography? *
    a. Yes
    b. No

28. Do you derive Photogrammetric Point Clouds from aerial photography? *
    a. Yes
    b. No
29. What product(s) does your company derive from Photogrammetric Point Clouds? *
    a. Digital Elevation Model (DEM)
    b. Canopy Height Models (CHM)
    c. Mean Top Height (MTH) estimates
    d. Stem count or stocking
    e. Stem volume estimates
    f. Biomass or carbon estimates
    g. Other (please specify):
30. For what applications do you use your aerial photography? *
    a. Cutover Mapping
    b. Fire Assessment
    c. Forest Health Assessment
    d. Harvest Planning
    e. Hazards
    f. Historic/Cultural Site Identification
    g. Hydrological Features
    h. Forest Inventory
    i. Landslide/Soil Displacement Assessment
    j. Road Mapping
    k. Silvicultural Planning
    l. Site Preparation
    m. Species Identification
    n. Stand/Forest Mapping
    o. Windthrow Assessment
    p. Other (please specify):
31. What are the factors that determine when you acquire aerial photography? * (e.g. We acquire aerial photography once a year or as needed, which is pre-harvest and post-harvest)
32. What is the spatial resolution of your aerial photography? * (e.g. 2 metres)

Aerial Videography

Aerial videography refers to motion pictures which consists of three bands (red, green, blue) and is acquired from an aerial platform (e.g. plane, UAV).

33. Does your company use aerial videography? *
    a. Yes
    b. No
34. What are the reasons for not using aerial videography? *
    a. Cost
    b. No perceived benefits
    c. Current staff lack of knowledge or training to use aerial videography
    d. Was not aware of aerial videography
    e. Other (please specify):
35. How is your aerial videography acquired? *
    a. Unmanned Aerial Vehicle (drone)
    b. Airplane
    c. Helicopter
    d. Other (please specify):
36. For what applications do you use your aerial videography? *
37. What are the factors that determine when you acquire aerial videography? * (e.g. We acquire aerial videography once a year or as needed, which is pre-harvest and post-harvest)

Multispectral Imagery

Multispectral imagery typically consists of four or more bands (red, green, blue, infrared, etc) and is commonly acquired from an airplane, UAV, or satellite.

38. Does your company use multispectral imagery? *
    a. Yes
    b. No
39. What are the reasons for not using multispectral imagery? *
    a. Cost
    b. No perceived benefit
    c. Current staff lack of knowledge or training to use multispectral imagery
    d. Was not aware of multispectral imagery
    e. Other (please specify):

40. How is your multispectral imagery acquired? *
    a. Airplane
    b. Satellite
    c. Unmanned Aerial Vehicle (e.g. drone)
    d. Helicopter
    e. Other (please specify):
41. If you acquire satellite imagery, which sensor(s) do you use? *
    a. Sentinel
    b. RapidEye
    c. Landsat
    d. PlanetScope
    e. Worldview
    f. Other (please specify):
42. What products does your company derive from the multispectral imagery? *
    a. True-colour composites (includes only red, green and blue bands (RGB))
    b. False-colour composites (including RGB and other bands)
    c. Vegetation Indices (e.g., Normalised Difference Vegetation Index (NDVI))
    d. Other (please specify):
43. If you use vegetation indices, which do you use? *
    a. Normalised Difference Vegetation Index (NDVI)
    b. Soil Adjusted Vegetation Index (SAVI)
    c. Burn Area Index (BAI)
    d. Enhanced Vegetation Index (EVI)
    e. Ratio Vegetation Index (RVI) also known as Simple Ration (SR)
    f. Other (please specify):
44. For what applications do you use your multispectral imagery? *
    a. Cutover Mapping
    b. Fire Assessment
    c. Forest Health Assessment
    d. Harvest Planning
    e. Hazards
    f. Historic/Cultural Site Identification
    g. Hydrological Features
    h. Forest Inventory
    i. Landslide/Soil Displacement Assessment
    j. Road Mapping
    k. Silvicultural Planning
    l. Site Preparation
    m. Species Identification
    n. Stand/Forest Mapping
    o. Windthrow Assessment
    p. Other (please specify):
45. What are the factors that determine when you acquire multispectral imagery? * (e.g. We acquire multispectral imagery once a year or as needed, which is pre-harvest and post-harvest)
46. What is the spatial resolution of your multispectral imagery? * (e.g. 10 metres)

Hyperspectral Imagery

Hyperspectral imagery typically contains hundreds of bands spanning the visible and infrared wavelengths. Hyperspectral imagery is acquired from an aerial or satellite platform.

47. Does your company use hyperspectral imagery? *
    a. Yes
    b. No
48. What are the reasons for not using hyperspectral imagery? *
    a. Cost
    b. No perceived benefits
    c. Current staff lack knowledge or training to use hyperspectral imagery
    d. Was not aware of hyperspectral imagery
    e. Other (please specify):
49. How is your hyperspectral imagery acquired? *
    a. Unmanned Aerial Vehicle (e.g. drone)
    b. Airplane
    c. Helicopter
    d. Satellite
    e. Other (please specify):

50. If you acquire hyperspectral imagery, which sensor(s) do you use? *
51. For what applications do you use your hyperspectral imagery? *
    a. Cutover Mapping
    b. Fire Assessment
    c. Forest Health Assessment
    d. Harvest Planning
    e. Hazards
    f. Historic/Cultural Site Identification
    g. Hydrological Features
    h. Forest Inventory
    i. Landslide/Soil Displacement Assessment
    j. Road Mapping
    k. Silvicultural Planning
    l. Site Preparation
    m. Species Identification
    n. Stand/Forest Mapping
    o. Windthrow Assessment
    p. Other (please specify):
52. What are the factors that determine when you acquire hyperspectral imagery? * (e.g. We acquire hyperspectral imagery once a year or as needed, which is pre-harvest and post-harvest)
53. What is the spatial resolution of your hyperspectral imagery? * (e.g. 3 metres)

LiDAR

LiDAR is an active remote sensing technique that stands for Light Detection and Ranging, it is also known as laser scanning.

54. Does your company use LiDAR data? * (this includes LiDAR-derived products such as Digital Elevation Models)
    a. Yes
    b. No
55. What are the reasons for not using LiDAR? *
    a. Cost
    b. No perceived benefits
    c. Current staff lack knowledge or training to use LiDAR data
    d. Was not aware of LiDAR
    e. Other (please specify):
56. How is your LiDAR data acquired? *
    a. Unmanned Aerial Vehicle (e.g. drone)
    b. Airplane
    c. Helicopter
    d. Satellite (e.g. Global Ecosystem Dynamics Investigation (GEDI))
    e. Static Terrestrial platform (e.g. LiDAR sensor mounted on tripod)
    f. Mobile Terrestrial platform (e.g. LiDAR sensor mounted on backpack or handheld)
    g. Vehicular platform (e.g. LiDAR sensor mounted on ute)
    h. Open data portal (e.g. Open Topography)
    i. Other (please specify):
57. If you acquire LiDAR, which sensor(s) do you use?
    a. DJI Zenmuse L1
    b. Emesent Hovermap
    c. Grenvalley LiAir series
    d. Leica BLK series
    e. Riegl laser scanners
    f. Other (please specify):
58. What are the factors that determine when you acquire LiDAR data? * (e.g. We acquire LiDAR data once a year or as needed, which is pre-harvest and post-harvest)
59. If you know, could you please provide the point density of the LiDAR data you acquire? * (e.g. 10 points/m^2)
60. How do you process the raw point clouds (i.e. las or laz files)? *
    a. We process the raw point clouds data in-house
    b. We engage a third-party organisation (e.g. surveying company or consultants) to process point clouds data
61. What do you do to process and analyse the raw point clouds? *
    a. Filtering and cleaning point cloud
    b. Classifying points to ground and non-ground points
    c. Classifying points to detailed classes (e.g., water, high vegetation, low vegetation)
    d. Generating surfaces (e.g., DEM, DSM, CHM)
    e. Detecting and segmenting individual trees
    f. 3D model construction of individual trees
    g. Deriving LiDAR metrics at plot-level

   h. Deriving LiDAR metrics at tree-level
   i. Other (please specify):
62. What product(s) does your company derive from LiDAR data collection and processing? *
   a. Canopy Height Model (CHM)
   b. Digital Elevation Model (DEM)
   c. Mean Top Height (MTH) estimates
   d. Stem count or stocking
   e. Stem volume estimates
   f. Biomass or carbon estimates
   g. Other (please specify):
63. If a DEM is derived, what spatial resolution is it?
64. For what applications do you use your LiDAR products? *
   a. Cutover Mapping
   b. Fire Assessment
   c. Forest Health Assessment
   d. Harvest Planning
   e. Hazards
   f. Historic/Cultural Site Identification
   g. Hydrological Features
   h. Forest Inventory
   i. Landslide/Soil Displacement Assessment
   j. Road Mapping
   k. Silvicultural Planning
   l. Site Preparation
   m. Species Identification
   n. Stand/Forest Mapping
   o. Windthrow Assessment
   p. Other (please specify):

Additional Remote Sensing Data

65. If you use any other types of remote sensing data for your forest management (e.g., radar), please specify the data type used, and the corresponding application.

Software

66. If you use imagery (including aerial photography, multispectral and/or hyperspectral) for your forest management, what software do you use to visualise and analyse each type of imagery? Please tick all the answers that apply.

Software	Aerial Photography	Multispectral Imagery	Hyperspectral Imagery
ATLAS GeoMaster			
ENVI			
ERDAS IMAGINE			
ESRI ArcGIS Desktop (e.g. ArcMap)			
ESRI ArcGIS Pro			
GDAL			
Global Mapper			
Google Earth Engine			
GRASS GIS			
Python			
QGIS			
R			
Trimble eCognition			

67. If your company uses any other software to visualise and analyse imagery, please list the software name, and the corresponding imagery.
68. If you use photogrammetry points, what software do you use to collect and process ***photogrammetry point clouds*** (creating point clouds from structure from motion)? Please tick all the answers that apply.
   a. Agisoft Metashape
   b. COLMAP
   c. DJI Terra
   d. DroneDeploy
   e. ESRI Drone2Map

f. LiMapper
g. Pix4Dmapper
h. Other (please specify):

69. If you use point cloud data (including photogrammetry and LiDAR) for your forest management, what software do you use to ***collect and process point clouds***? Please tick all the answers that apply.

Software	**Photogrammetry point cloud**	**LiDAR point cloud**
Cloudcompare		
Computree		
DJI Terra		
Fusion		
LASTools		
LiDAR360		
Python		
R - LidR package		
R - other packages		

70. If your company uses any other software to ***collect and process*** photogrammetry and/or LiDAR point clouds please list the software name, and the corresponding point cloud type (i.e. LiDAR or photogrammetry).

Artificial Intelligence

Artificial Intelligence (AI) is a technology that enables computers to perform tasks with human-like intelligence, such as analysing data, making decisions, and solving problems. It can include methods such as machine learning and deep learning.

71. Does your company use AI when working with geospatial data? *
    a. Yes
    b. No
72. What are the reasons for not using AI? *
    a. Cost
    b. No perceived benefits
    c. Current staff lack knowledge or training to use AI models
    d. Was not aware of AI models
    e. Other (please specify):
73. What AI models does your company use? * (e.g. Random Forest or Convolutional Neural Network)
74. What types of remote sensing data is used in AI models? *
    a. Aerial Photography
    b. Multispectral Imagery
    c. Hyperspectral Imagery
    d. LiDAR
    e. Other (please specify):
75. For what applications do you use AI? *
    a. Cutover Mapping
    b. Fire Assessment
    c. Forest Health Assessment
    d. Harvest Planning
    e. Hazards
    f. Historic/Cultural Site Identification
    g. Hydrological Features
    h. Forest Inventory
    i. Landslide/Soil Displacement Assessment
    j. Road Mapping
    k. Silvicultural Planning
    l. Site Preparation
    m. Species Identification
    n. Stand/Forest Mapping
    o. Windthrow Assessment
    p. Other (please specify):
76. Thank you for completing the survey. Would you like to receive a copy of the final report?
    a. Yes
    b. No