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UAV Survival Assessments: RGB Ortho-plotting

Summary:

UAVs can be utilised as a cost-effective alternative to field plotting for foresters who are constrained by labour shortages or budget. In this report, we assess a method of conducting orthomosaic plotting (ortho-plotting) to conduct survival surveys across two recently planted stands of *Pinus radiata* using a DJI Phantom 4 Pro. This study compares both manual annotation and automating seedling counting methodologies to obtain stocking and comparing this with field-based plotting to determine accuracy. UAV data was captured at four altitudes to assess the impact of image quality (ground sampling distance/GSD) on stocking accuracy. In addition, a time study was conducted to obtain some insight into potential gains in field data capture efficiencies using these methods. The report found that manual annotation methods delivered the best accuracy and recall (76% and 85% respectively). Automated methods performed less well, with accuracy and recall of 41% and 45% respectively. It was also found that site characteristics had a significant impact on results, particularly for automated methods. Neither approach was as accurate as field-based, but trade-offs are discussed as there is potential to capture three- to fourfold more plots per day using these methods when compared with field-based plotting. It is hoped that this study will help foresters to determine appropriate flight parameters for conducting these operations and to determine whether these methods would be suitable for their own mensuration needs.

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Introduction

In forestry, survival assessments are an important part of the post-establishment cycle. These assessments provide foresters crucial information regarding tree survival rates, missing trees, stocking irregularities, and overall stand condition and health. Traditionally, survival assessments have been carried out through field-based assessments, which can at times be a very arduous task, working in unpleasant conditions and challenging environments, conducting labour-intensive processes to obtain the required metrics. Furthermore, survival assessments typically require a minimum two-person team.

A potential alternative method to field-based operations is using UAVs as a tool for collecting this data. There is currently a lack of information available for foresters on how to conduct forestry operations using UAVs. As UAV technology develops, the number of powerful products and user-friendly apps continues to expand, providing an important range of resources from which foresters can take benefits.

This study seeks to assess the efficacy of prosumer-grade UAVs as a survival assessment tool. UAVs of this class can efficiently capture the necessary imagery required to produce an orthomosaic: a map composed of multiple overlapping images. This can then be analysed in a geographic information system (GIS) to count seedlings and obtain stocking or assess health as per traditional field-based survival assessments. As seedlings are small, relatively high-resolution imagery is required to be able to resolve them in sufficient detail for detection. With the prosumer grade UAVs, this means flying low and slow and therefore makes total site capture unfeasible. A way to make this technology more operational is to use UAVs to conduct a series of smaller flights at prescribed locations across the site. This generates a series of small orthomosaics which we refer to as "ortho-plots", emulating the traditional field-based sample plot methodology.

An important factor when evaluating flight altitudes is the change in ground sampling distance (GSD). As a UAV gains altitude, GSD grows larger with it (Figure 1). GSD can be considered as the distance between the centres of neighbouring pixels of a captured image (Lee, et al., 2019). As the UAV gains altitude, the size of the pixel increases, ultimately leading to greater loss of usable detail, definition and clarity in captured imagery.

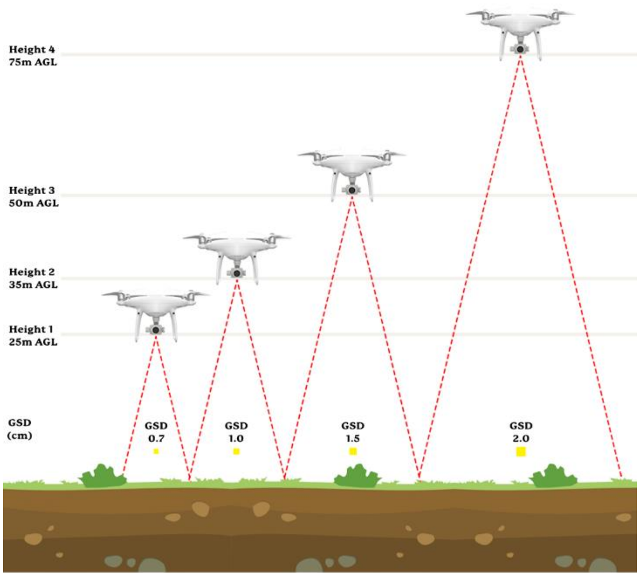

Figure 1. Diagram displaying the relationship with the increase in altitude with the increase in GSD utilising the altitudes assessed in this report.

To assess stocking, firstly the seedlings need to be detected. In this project, two seedling detection methods were trialled to assess their viability: manual annotation within a GIS, and automatic detection using a commercially available service.

Objective

This project specifically focuses on the efficacy of two different seedling detection methods for ortho-plotting compared to traditional field-based plotting. These include:

- Manual ortho-plotting
- Automatic ortho-plotting

Additionally, this project aims to assess the time efficiencies of these methods, and how the altitude/ GSD of the UAV affects the accuracy of the derived metrics.

Methods

For this project, two ~24 ha recently established forestry sites (Figure 2) were studied. Sites were chosen for their varying terrain and slope classes and to be of a suitable size that was largely representative of a mid-sized operational stand. Both sites are managed by Manulife Forest Management (NZ) Ltd (MFMNZ). The first site, located in Kinleith Forest, Waikato, consists of flat to rolling terrain, with a consistent minor downward gradient running from North to South. The second site, located in Pipiwai Forest, Northland features steeper terrain.

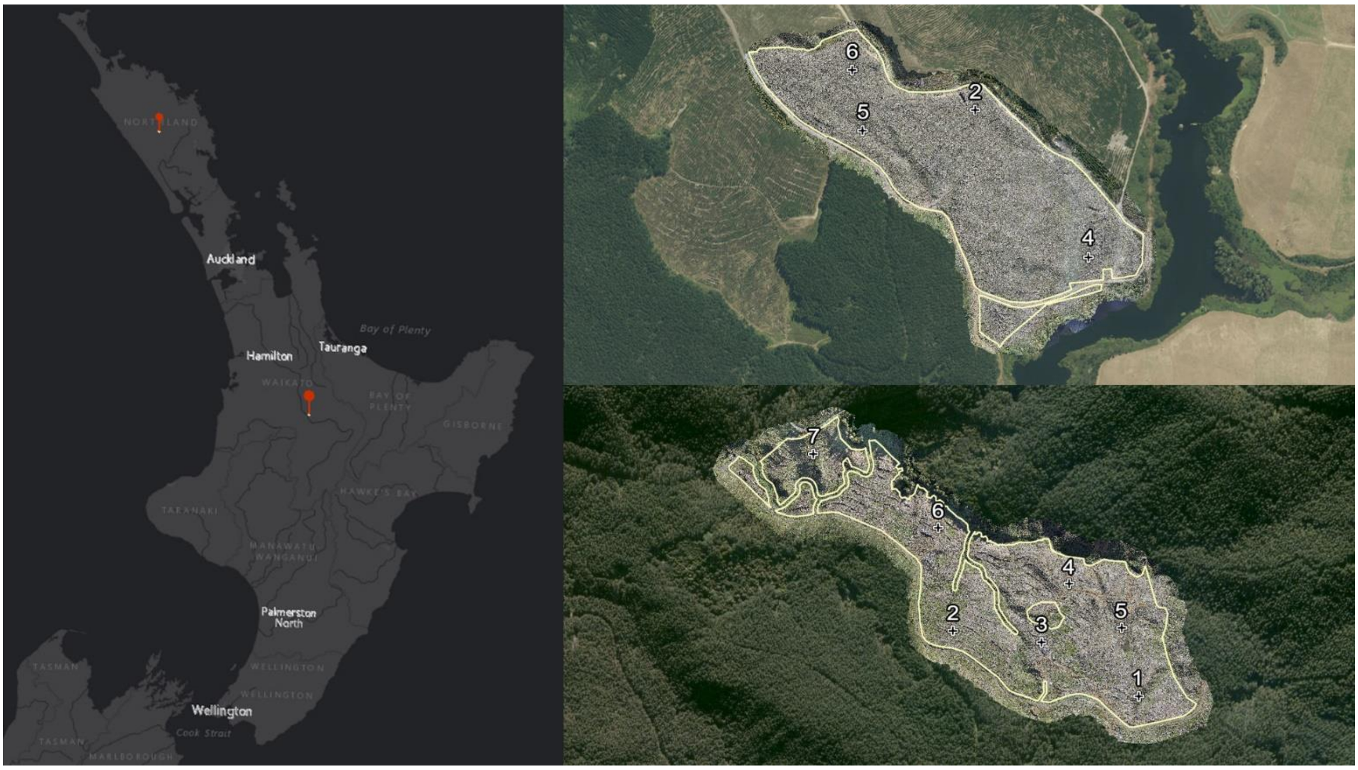

Figure 2. Map of the two locations used for this study (red pins with Pipiwai to the north and Kinleith in the central North Island region). Upper right map displays the Kinleith Forest site in the Waikato, lower right showing the Pipiwai Forest site in Northland, with numbered crosses representing the location of the sample plots. Only plots from which orthomosaics were successfully derived are displayed (see Data processing section).

Field data capture methods

For this project, ground truth data was collected using traditional field-based plotting methods. In Pipiwai Forest, Northland, plotting was conducted by Forest Protection Services Ltd. Plotting recorded tree count, stocking gap and health status data from seven 0.02 ha plots, evenly spaced across the study site.

In Kinleith Forest, students from Toi-Ohomai Institute of Technology, Rotorua, supervised by James Broadley (tutor), assessed and recorded tree count and health status data from six 0.06 ha plots, evenly spaced across the study site. These plots were mistakenly measured to the wrong size, but this should have little to no bearing on the final result.

All plot centres were marked either with a high contrast ground control target or spray paint so that they could be located in the UAV imagery. Each team then independently digitised these findings for reference as the primary ground truth layers.

Remote sensing capture methods

For this project, the aircraft assessed was the DJI Phantom 4 Pro (DJI, Shenzhen, China). This aircraft is a widely used prosumer-grade UAV within the forestry industry and has a proven track record for forestry applications (Dhruva, et al.; Hartley, et al., 2020; Jayathunga, et al., 2023; Krisanski, et al., 2020). The DJI Phantom 4 Pro has a 20MP 1-inch integrated sensor, and was utilised to capture high overlap visual imagery (red/green/blue, RGB) datasets at four different altitudes; 25 m, 35 m, 50 m and 75 m above ground level (AGL; Figure 1) above the centre of each of the 13 sample plot locations, in both Pipiwai and Kinleith Forests. Flight specifications can be found in Table 1.

Table 1. Flight specifications for data captured at different altitudes for ortho-plotting.

Altitude AGL (m)	GSD (cm)	Overlap (forward:side)	Flight speed (m/s)
0.7	25	80:80	1.5
1	35		2
1.5	55		3
2	70		4

Forest Protection Services (FPS) Geospatial Ltd, Whangārei, collected the remote sensing data in Pipiwai Forest, and a team of students from Toi Ohomai Institute of Technology, Rotorua, collected the remote sensing data in Kinleith Forest. FPS Geospatial utilised UGCS (SPH Engineering, Riga, Latvia), and Toi-Ohomai utilised Map Pilot Pro (Drones Made Easy, San Diego, CA, USA) for their flight planning and control software to perform data capture.

For each of the 13 plots across the two study sites, a series of small photogrammetry flights, was captured at each of the four target altitudes.

Data processing

Once all data was captured in the field from each of the 13 sample plots, Pix4Dmapper was chosen as the photogrammetric software to process and generate the RGB orthomosaics required for this project (Figure 3). Default processing settings within Pix4D were used with the exception of geometrically verified matching being turned on. Resulting orthomosaics were exported in a single, merged GeoTIFF format.

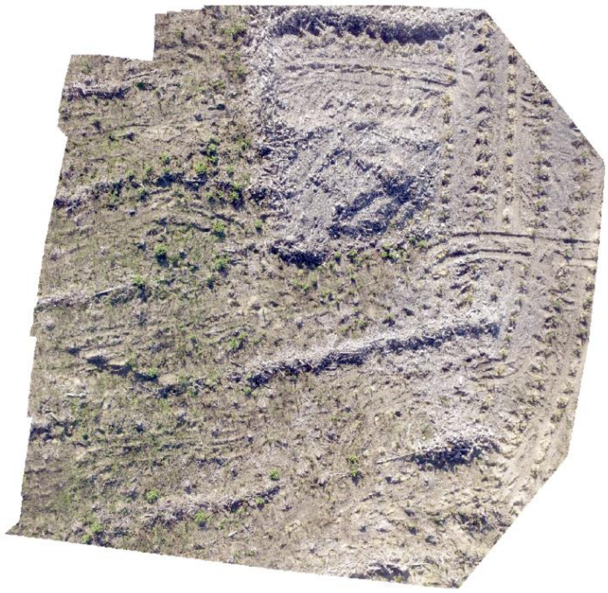

Figure 3. Kinleith Forest Plot 2 50m RGB Orthomosaic produced by Pix4D from photogrammetry data.

The orthomosaics produced for all seven Pipiwai Forest sample plots using the data from each of the four altitudes were successfully created. Due to issues with the data capture software and GPS anomalies experienced during the Kinleith data capture, only four of the six sample plots from the Kinleith Forest photogrammetry data could be successfully transformed into orthomosaics (Figure 2).

Data analysis

Once obtained from Pix4D, the orthomosaic files were loaded into ArcGIS Pro v3.0.0 (ESRI Inc., Redlands, CA) for analysis. ArcGIS Pro was selected for this project as it offers a versatile suite of geospatial tools essential for the comparison of the two different seedling detection methods.

Manual ortho-plotting

To assess the various UAV data, orthomosaics for each plot at the four altitudes were loaded into the GIS. Next, plot centres were located from the imagery and annotated in the GIS. Plot boundaries were then digitised by adding a circular buffer to each plot centre that correctly represented the size used in the field surveys (Pipiwai 0.02 ha and Kinleith 0.06 ha). Finally, each seedling within the plot boundary was manually annotated, producing a total 44 separately annotated datasets. An example of a manually annotated orthomosaic can be found in Figure 4a.

Automatic seedling detection

For the second method of analysis, a commercially available automatic seedling detection service was utilised. Orthomosaics were sent to Indufor Asia Pacific Ltd, Auckland, who applied their proprietary deep learning algorithms to the data. Their deep learning algorithms automatically detect and label the location of tree seedlings within an orthomosaic. After this process, the seedling locations were output as spatial point layers in .SHP format.

These point layers were then loaded into ArcGIS Pro, analysed for anomalies, and clipped so that only detections within the plot boundaries remained, ready for further analysis (Figure 4b)

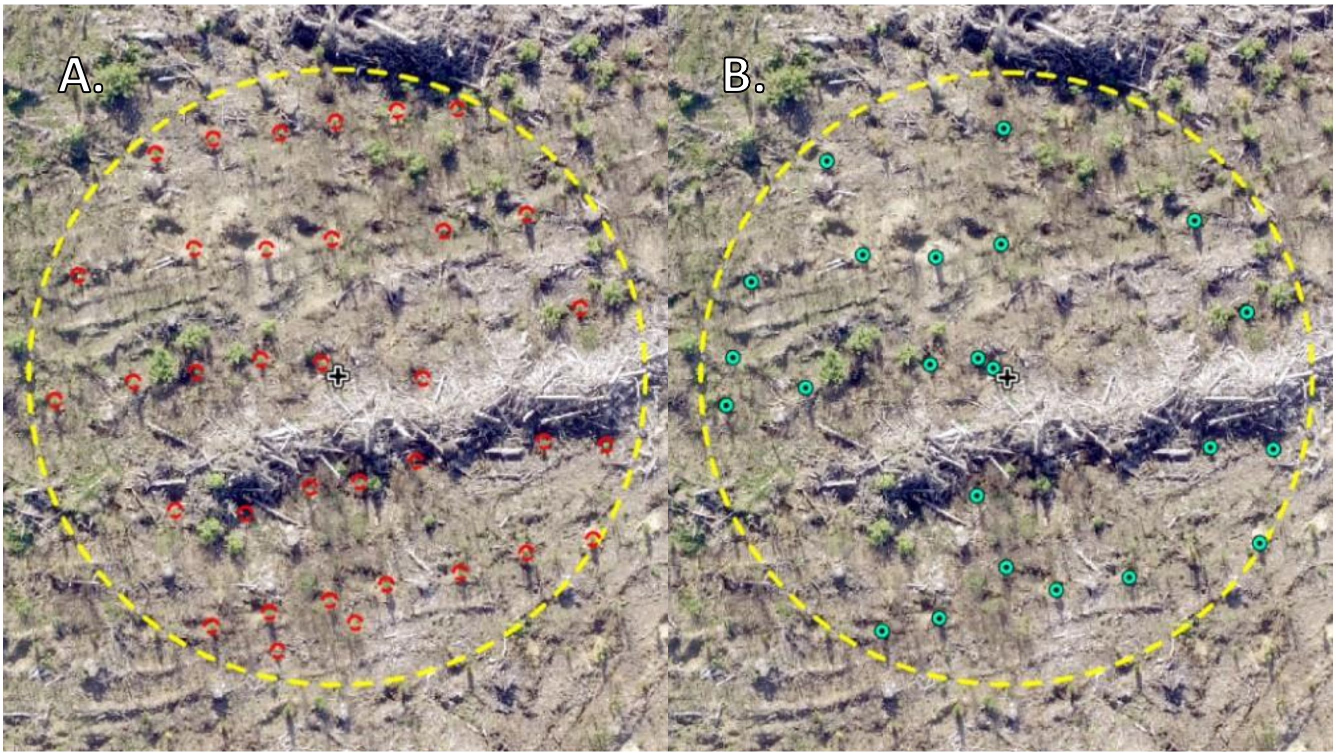

Figure 4. Example of annotations for Kinleith Forest plot 2 on a 1 cm GSD orthomosaic with a. manually annotated and b. automatically detected seedlings. Figures show plot boundaries (yellow), plot centres (black crosses), manual seedling annotations (red) and automatic seedling detections (cyan).

Statistical methods

To determine the efficacy of the two seedling detection methods for ortho-plotting, metrics for accuracy (I), precision (II) and recall (III) were made using the previously produced omissions and commissions.

To calculate these metrics, the following formulas were used:

$$\text{I.} \quad Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

$$\text{II.} \quad Precision = \frac{TP}{TP + FP}$$

$$\text{III.} \quad Recall = \frac{TP}{TP + FN}$$

Accuracy represents the number of seedlings that were correctly identified as seedlings. Precision is the proportion of positive seedling identifications that were correct, taking into account the number of objects falsely identified as seedlings. Recall is the proportion of the positively identified seedlings that were correctly identified, taking into account the number that were missed.

A confusion matrix (Figure 5a) was created to determine the classification of each detection point. Detection classifications were then used to predict metrics for accuracy, precision and recall for each method including:

True positive (TP) – a seedling, correctly identified as a seedling.
False negative (FN) – a seedling, not identified as a seedling.
False positive (FP) – Not a seedling, Identified as a seedling.
True negative (TN) – Not a seedling, not identified as a seedling.

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To determine the classification of each point, the digitised field data was assigned an individual tree number (Figure 5d), which served as the ground truth of which seedlings were really present on the ground.

The manual annotations and automatic detections were then assigned an individual tree number to match those of the field data and comparisons with this ground truth data were made to determine detection classifications.

Using the example plot given in Figure 5, the automatic detections produced 11 TP, 0 FP, 10 FN and 0 TN (Figure 5b) and the manual annotations produced 20 TP, 1 FP, 1 FN and 0 TN (Figure 5c)

A total of 44 sets of detection classifications were obtained for the automatic detection samples, and 44 sets of detection classifications were produced for the manual annotations.

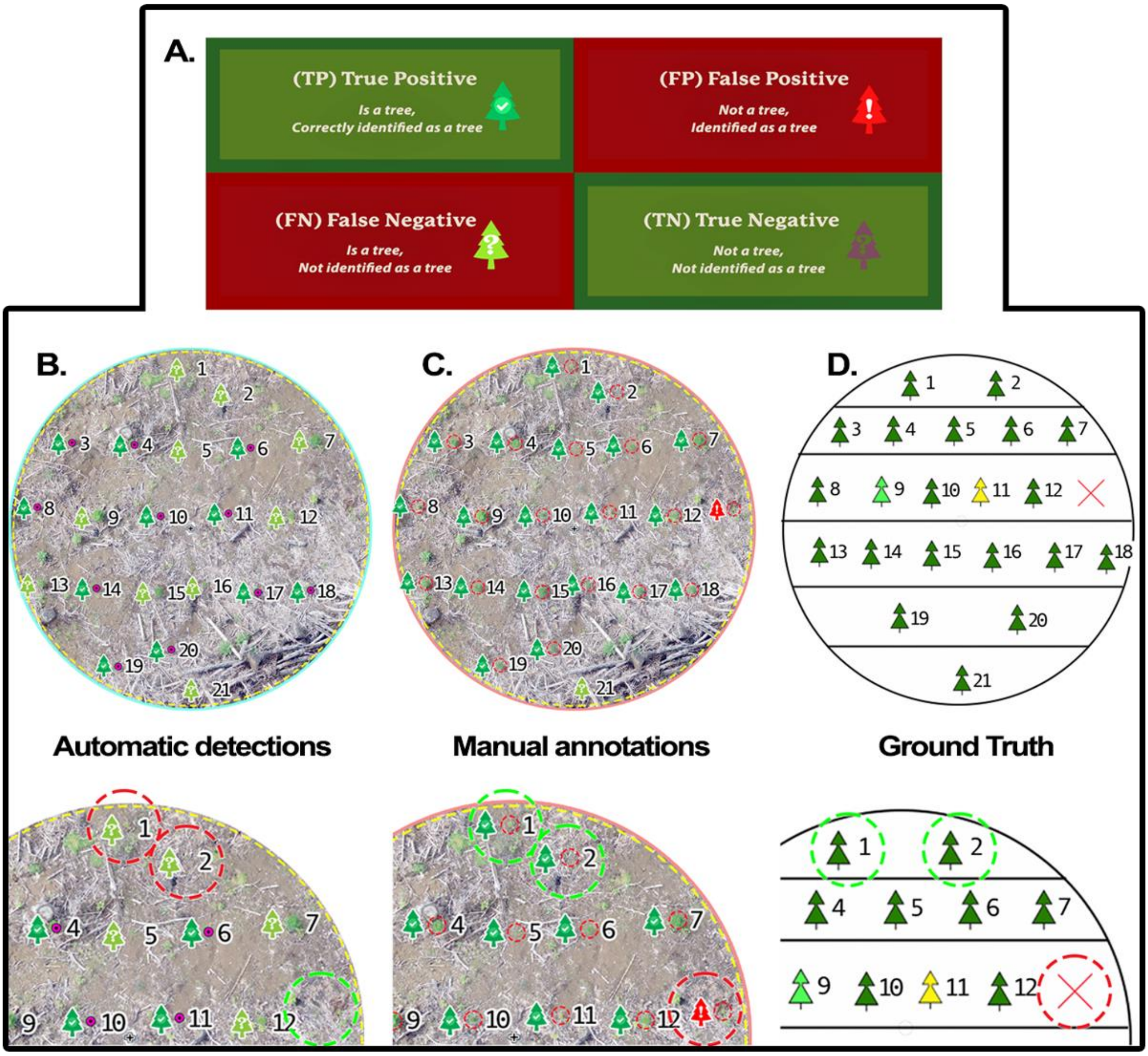

Figure 5. Graphical explanation of the accuracy assessment methodology: (a.) an example of a confusion matrix featuring detection classifications, methods for comparing automatic (b) and manual detections (c.) to field data (d). Close up images show examples of FN (b.; light green trees with red circles), TP (c.; dark green trees with green circles and FP (c.; red tree, red circle).

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Table 2. Prediction metrics for automatic detections and manual annotations averaged across all plots according to site. The overall best performing resolution (GSD) dataset for each site is highlighted in green.

Site	Method	GSD	Mean accuracy (%)	Mean precision (%)	Mean recall (%)
Combined	Automatic detections	0.7 cm	41	94	45
		1 cm	38	91	40
		1.5 cm	38	93	41
		2 cm	37	91	40
	Manual annotations	0.7 cm	76	89	85
		1 cm	74	87	83
		1.5 cm	73	89	80
		2 cm	72	93	77
Pipiwai Forest	Automatic detections	0.7 cm	27	100	27
		1 cm	21	90	22
		1.5 cm	30	95	32
		2 cm	23	92	24
	Manual annotations	0.7 cm	77	88	87
		1 cm	71	86	80
		1.5 cm	72	90	78
		2 cm	70	92	75
Kinleith Forest	Automatic detections	0.7 cm	65	83	77
		1 cm	67	92	72
		1.5 cm	53	91	56
		2 cm	62	90	67
	Manual annotations	0.7 cm	74	90	83
		1 cm	81	90	89
		1.5 cm	75	89	83
		2 cm	76	94	81

Results

Indufor's commercial automatic seedling detection service was directly compared to manual ortho-plotting using the 88 total sets of omissions and commissions produced in this study.

Overall, the 0.7 cm GSD data provided the best resolution dataset for both automatic detections and manual annotations when results were combined from both sites. Manual annotation performed better than automatic detection (accuracy = 76%, precision = 89% and recall = 85%, and accuracy = 41%, precision = 94% and recall = 45% respectively).

At each site, and across both sites, manual annotations performed better in terms of accuracy (range 70-81%) and recall (range 77-89%) than automatic detections (ranging from 21-67% accuracy and 22-77% recall). Interestingly mean precision was generally higher for automatic detections aside from the 0.7 cm and 2 cm GSD data at Kinleith Forest, and the 2 cm GSD data at Pipiwai Forest (where precision was the same for both methods).

Results for all metrics were generally better for manual and automatic methods at Kinleith Forest than Pipiwai Forest. It is interesting to note that the difference between the two sites is more pronounced with the automatic detections than the manual annotations.

A significant increase was observed in the operational time to capture data at a plot-level between the optimal and slowest flight altitudes. Calculations for time taken to capture a single plot were ~1.5 minutes quicker at 55 m AGL than at 25 m AGL (Table 3). This equated to a difference of ~13 plots in an eight-hour period (Table 3).

Table 3. Time study assessing impact of GSD and altitude on flight time, work rate, accuracy and recall. Adjusted flight rate was calculated by doubling the approximate flight time as stated in the Map Pilot Pro app to complete a flight that covers ~0.25 ha. This was considered to be an area that would adequately cover a 0.06 ha plot plus a suitable buffer. Plots per day is the number of plots that could be conducted in an 8 hour working day based on the adjusted flight time, not taking into account travel to the forest, set up and pack down time, or time to move to a different site.

Method	GSD (cm)	Altitude AGL (m)	Approx flight time per plot (mm:ss)	Adjusted flight time per plot (mm:ss)	Plots per day	Mean accuracy (%)	Mean recall (%)
Automatic detections	0.7 cm	0.7	06:20	12:40	38	41	45
Manual annotations						76	85
						loss in accuracy (%)	loss in recall (%)
Automatic detections	1 cm	1	05:30	11:00	44	3	5
	1.5 cm	1.5	04:46	09:32	51	3	4
	2 cm	2	05:09	10:18	46	4	5
Manual annotations	1 cm	1	05:30	11:00	44	2	2
	1.5 cm	1.5	04:46	09:32	51	3	5
	2 cm	70	05:09	10:18	46	4	8

Discussion

On average across all 11 plots at both sites, in terms of accuracy and recall, the 0.07 cm GSD provided the best results for both manual annotation and automatic detections. When looking at individual sites, however, the best results at Kinleith for both methods was obtained using 1 cm GSD imagery, while at Pipiwai manual annotation performed best using 0.7 cm GSD imagery whereas automatic detections performed best with 1.5 cm GSD imagery. This suggests that both methods are impacted by site characteristics, however, it is generally better to choose a higher resolution data set to ensure better results overall.

Mean accuracy and recall values for automatic seedling detection was, in general, considerably lower than that of manual ortho-plotting, although automatic seedling detection achieved a greater average precision. These results indicate that the automatic detection method is on the whole better at returning true seedling detections, however, manual annotation returns a greater number of accurate detections. When separating findings into site specific averages it is clear that the automatic detection data from Kinleith Forest greatly outperformed that of Pipiwai Forest, lending support to the argument that site characteristics have a significant impact on results, especially for automatic detections.

For automatic detections alone, detections from Pipiwai Forest, across all flight altitudes, returned an average accuracy range of 21-30%, an average precision range of 90-100%, and an average recall range of 22-32%. Detections from Kinleith Forest, across all flight altitudes, returned an average accuracy range of 53-67%, an average precision range of 83-92%, and an average recall range of 56-77%.

A number of site-specific variables can contribute to the success of results collected in the field. There are a number of variables that can impact on detection accuracy including amount of harvest residue, and cover, size and species of weed species (Finn, et al., 2022; Jayathunga, et al., 2023; Pearse, et al., 2020). In addition, time of day, shadows and overall lighting conditions when the UAV photogrammetry data is collected can also impact on the quality of the imagery and the ability of detection algorithms to perform on it. Table 4 shows the site conditions prevalent at both sites.

Table 4. Site characteristics and lighting conditions observed at each site.

Site characteristic and lighting	Pipiwai Forest	Kinleith Forest
Weed growth	heavy	light
Logging debris	light	heavy
Spot mounding	no	yes
Lighting conditions	flat/diffuse	high contrast
Shadow cast	low	high

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When comparing the average terrain and vegetation found at Pipiwai and Kinleith Forests (Figure 6) there are clear differences, and a number of the aforementioned variables could have played a role in the varying success of the captured data.

Figure 6. Average terrain and vegetation cover examples from Pipiwai Forest (a) and Kinleith Forest (b).

Recommendations

This study has demonstrated that stocking can be assessed from UAVs with a high level of precision and accuracy using automatic detection and manual ortho-plotting methods, albeit not as accurately as field-based plotting. This study has focused on stocking alone and, therefore, at this stage the assessed UAV methodology cannot acquire the additional metrics for tree health and condition. There are, however, other benefits to using RGB ortho-plotting beyond what has been covered by this study.

Traditionally, survival assessments have been carried out on the ground, which is a time consuming and laborious task. These assessments can involve unpleasant conditions, challenging environments, and labour-intensive processes to obtain the required data. Furthermore, survival assessments typically require a minimum two-person team. UAV remote sensing methods can be less labour-intensive than field-based plotting as they can be conducted with only one person. There is also an improvement to health and safety when UAV operators do not need to walk through the cutover to carry out the plotting work (although there is still need for some site preparation, prior to flight).

Additional data can also be captured with UAVs that can be used for various planning and operational tasks. Alongside high-resolution imagery, point clouds can be generated, creating 3D models that can be used to assess terrain for roading and forest engineering. In addition to stocking counts, weed cover can be assessed from imagery (De Castro, et al., 2018), health status can be assessed (Fraser, et al., 2021), and regenerating seedlings (regen) can be distinguished from planted seedling using point clouds (Jayathunga, et al., 2023). Future research should look to expand on this study by assessing a more comprehensive ortho-plotting technique which brings together some of these additional applications.

The time study shows a significant increase in the time taken per plot to capture data. Using the approximate time calculated in the Map Pilot Pro app, the quickest flight (55m AGL), was ~1.5 minutes faster per plot than the highest resolution/slowest flight (25 m AGL; Table 3).

Anecdotally it takes approximately twice the time estimated in the app to complete one plot mission, due to battery changes, checking the craft, taxi time to the plot etc. Using this logic, an adjusted rate per plot was used to calculate an approximate number of plots per eight-hour day (Table 3). The difference between the quickest (55 m AGL) and the slowest (25 m AGL) was 13 plots in a day (Table 3). These calculations are approximate and do not take into account travel to and from the field, set up and pack down time, time to travel between sites or longer taxi times if plots are located more than 1-200 m from the ground station.

According to our calculations, it can then be considered that an additional 13 plots could be achieved per day with associated losses in accuracy and recall of 4% and 8% for manual ortho-plotting, and losses of 4% and 5% for automatic detection (albeit with overall lower rates of accuracy and recall than for manual methods).

The Tools For Foresters committee provided an estimate that ~12 plots could be measured by field-based methods in an eight-hour day. When compared with the number of plots that can be achieved by a UAV in that timeframe (38-51) there is potential for a three- to four-fold increase in productivity. This doesn't take into account time taken to process and analyse the data and does not include health status assessment. Regardless, this demonstrates the potential for significant reduction in fieldwork time.

Of note, the quickest flights in the time study were not the highest altitude flights (Table 3). This is due to the small area requiring the same number of flight lines, but the UAV having to climb additional altitude to get the required GSD. For a larger flight mission, this would not be the case as the additional time to climb to altitude would be offset by a greater number of flight lines (Figure 7).

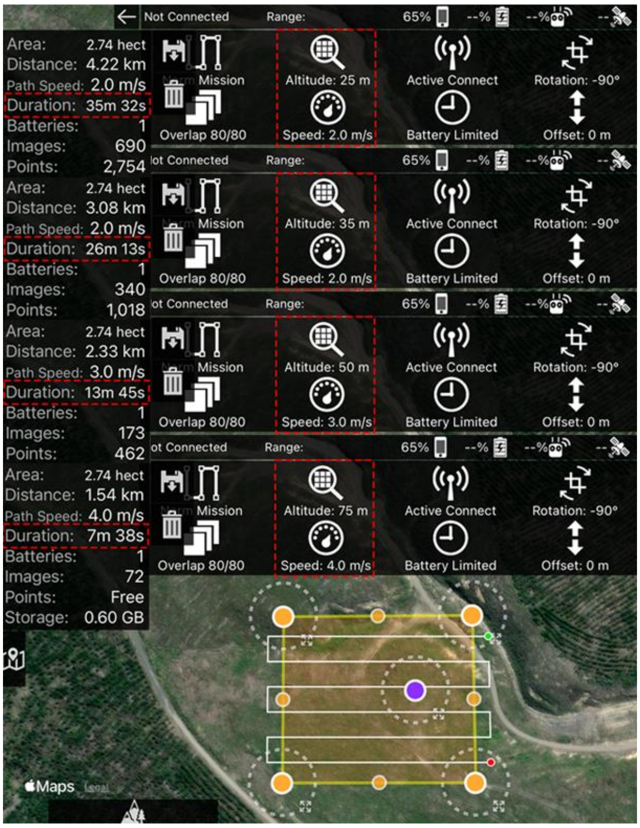

Figure 7. An example of how UAV flight duration, overall flight distance and image count (photogrammetric data captured) decreases with elevation gain over an identical 2.74 ha flight area. Note, the number of flight lines in the bottom image would increase in line with the increase in elevation.

Flight distance and duration generally decrease with altitude gain (Figure 7) meaning faster data capture at higher altitudes, resulting in less time spent flying overall. However, it is important to note that this report has also found that accuracy and recall decrease with altitude gain, meaning there is a primary trade-off between the quality of data captured and time duration of planned flights.

Conclusion

The findings of this report show a strong relationship between lower altitudes and higher accuracy, precision and recall. Consequently, there is an associated decrease in the number of plots attainable within a day as accuracy increases. For foresters looking to utilise the methods covered in this report, there will be trade-offs to consider when planning operations and it is hoped that this report will enable them to determine an appropriate resolution to meet their requirements.

This method of ortho-plotting using a DJI Phantom 4 Pro shows a lot of promise as an alternative to field-based plotting for foresters who are working with limited resources. This system would be ideal for foresters facing labour shortages or budget constraints where large areas of forest land need to be assessed. This is a user-friendly method that can produce quality results in a reliable and efficient manner.

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