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UAV Survival Assessments: the value of wall-to-wall site capture

Summary: This study investigates the efficacy of 100% site capture or "wall-to-wall" mapping using unmanned aerial vehicles (UAVs) equipped with high-resolution cameras for forest survival assessments. UAV imagery was captured at two altitudes, resulting in resolutions of 0.7 cm and 1 cm. Orthomosaic maps were generated from the imagery and stocking was derived using manual annotation within a geographical information system (GIS), and a commercial seedling detection service. Comparisons with field plots revealed high levels of precision, accuracy and recall for manual annotation (95%, 99% and 9% respectively) and automatic detection on 1 cm imagery (79%, 88% and 88% respectively). Lower results were observed from the 0.7 cm imagery, however, reasons for this are discussed alongside potential ideas for improving the accuracy of the automatic detections in general. A significant discrepancy between plot-based and wall-to-all methods when calculating average stocking at the stand level was also observed. Supplementary benefits of the wall-to-wall methodology, including cost and time efficiencies are explored, indicating that overall wall-to-wall data capture holds a lot of promise for foresters conducting survival surveys.

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1. Introduction

"Wall-to-wall" mapping, also referred to as 100% site capture, has existed for many years, however, until recently, data was captured by larger piloted aircrafts and/or satellites at high costs and at much lower resolutions. As many unmanned aerial vehicles (UAVs) are now equipped with high resolution cameras, it is increasingly feasible to fly small to medium scale areas of up to ~1-200 ha in a single operation and collect high resolution data using relatively accessible tools.

Forest mensuration is an area of forestry that heavily utilises the capabilities of remote sensing and increasingly UAVs for data capture. Wall-to-wall remote sensing in modern forest inventory is sometimes referred to as "enhanced" forest inventory as it can be utilised in many ways (Chirici et al., 2020, Stinson and White, 2018).

Until recently, high resolution (sub 2 cm) imagery was difficult for forestry companies to capture over larger areas as the UAVs that were readily available had lower resolution cameras (20 MP or less). In order to attain data at this resolution, the craft would have to fly low, resulting in a small ground footprint of the imagery. This meant that the distance between flight lines to achieve the required overlap was very short, resulting in impractical flight times. Attaining sub-cm imagery also meant flying close to the ground which caused issues with maintaining line of site in steep terrain, and causing safety concerns where neighbouring stands contain taller trees. With the advent of commercial UAV platforms with high resolution lenses, such as the DJI P1 (DJI, Shenzhen, China) with its 45 MP lens, it became possible to achieve sub-cm imagery whilst still flying at a safe altitude (>50 m) and increasing the distance between flight lines.

This study looks at the benefits of using high resolution UAV remote sensing to capture wall-to-wall imagery for conducting survival surveys. This method enables industry users to effectively capture and utilise data to assist with planning, decision making, and optimisation of resources.

Implementing wall-to-wall site capture for survival assessments in forestry has the potential to reduce the need for manual surveys, leading to considerable savings in costs and time (Feduck et al., 2018).

2. Objective

The aim of this study is to assess the value of wall-to-wall site capture for conducting survival surveys by comparing the effectiveness of capturing high resolution UAV data with traditional field plots. To this end this study had three objectives: (i) to assess the accuracy of seedling detection from UAV imagery through both manual annotation and automated detection methods; (ii) to compare stand stocking calculations derived from plotting with those derived from the wall-to-wall data; and (iii) to conduct time and cost analyses of UAV-based seedling detection compared with field plotting to assess the efficiency of both methods.

3. Methods

Two trial sites of approximately 24 ha each were identified for this project. Data was captured at each site using two methods. The first method consisted of traditional field plotting, whilst the second method utilised a UAV to capture high resolution imagery of the entire stands at two different altitudes to test the impact of altitude/resolution on seedling detection. Due to technical difficulties with one site, and time constraints to write up this report, the decision was made to focus on one site in more detail.

3.1. Study site

The study site used for this project was located on Topaz Road in Kinleith Forest, Waikato (Figure 1). The Topaz Road site consisted of flat to rolling terrain and is managed by Manulife Forest Management (NZ) Ltd (MFMNZ). The site was planted in September 2022 and was 11 months old at the time of the UAV data capture.

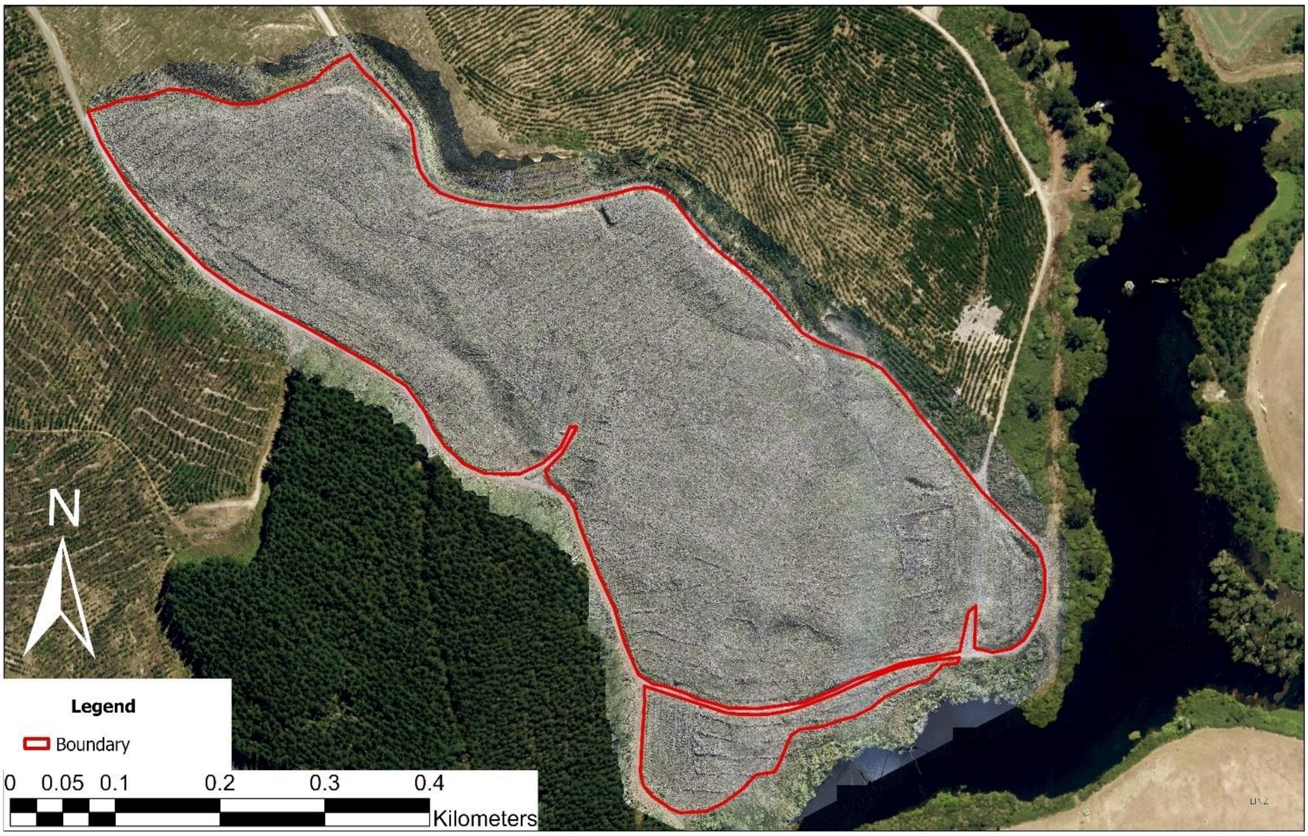

Figure 1. Site map for the Topaz Road forest site in Kinleith Forest. Orthomosaic imagery for the site is shown overlaid on regional imagery.

3.2. Field data capture methods

The field data for Topaz Road was captured by students from Toi Ohomai Institute of Technology, Rotorua, using ArcGIS Survey123 (ESRI, Redlands, CA, USA) on a mobile device. The field data capture consisted of six pre-determined 0.06 ha circular plots. In each plot the students recorded plot location (georeferenced via mobile device), tree number and tree condition (vigorous, alive, dying, dead and gone).

3.3. Remote sensing capture methods

The UAV data was collected using a DJI Matrice 300 RTK UAV (DJI, Shenzhen, China) equipped with a 45 MP DJI Zenmuse P1 camera (DJI, Shenzhen, China).

To assess the impact of ground sample distance (GSD; resolution) and flight efficiency on the results, two datasets were captured at altitudes of 55 m and 85 m above ground level (AGL). Flights were planned and flown by Scion using the DJI Pilot 2 app (DJI, Shenzhen, China) using the same parameters for speed, and overlap (Table 1). Ground control points were not utilised as the Matrice 300 comprises a high accuracy real time kinematic (RTK) global navigation satellite system (GNSS), which improves the spatial accuracy of imagery and resulting photogrammetric products.

Table 1. Flight parameters for UAV data capture at Topaz Road site.

Craft	Altitude (AGL; m)	Speed (m/s)	Approx GSD (cm)	Overlap (forward:side)	Planned Flight Time (hh:mm)
DJI Matrice 300 RTK	55	5	0.7	80:80	01:15
	85		1		01:00

3.4. Data processing

Field plot survey results
The field data collected through ArcGIS Survey123 was uploaded to ArcGIS Online (ESRI, Redlands, CA, USA). Field data were output from Survey123 as georeferenced shapefiles containing seedling-level data as attributes were then uploaded to ArcGIS Pro v.3.2.2 (ESRI, Redlands, CA, USA).

Orthomosaics
The images from each data set were processed into orthomosaics using Pix4DMapper (Version 4.8.4; Pix4D, Lausanne, Switzerland). Default processing settings were utilised with the exception of geometrically verified matching being enabled. Resulting orthomosaics were exported as a single, merged GeoTIFF.

Commercial seedling detection
The resulting orthomosaics were sent to Indufor Asia Pacific Ltd, Auckland, who applied their proprietary deep learning detection algorithms to each dataset for seedling detection analysis. A point data set, representing the location of each seedling that was detected, was exported in shapefile format.

3.5. Data analysis

Analysis for all data, including field data shapefiles, orthomosaics, and seedling detection point data from Indufor, was conducted using ArcGIS Pro.

Field data
The field data was analysed through Survey 123 to determine the total number of trees recorded per plot and used as the “ground truth”.

Manual seedling annotation plots
To assess the efficacy and accuracy of commercial seedling detections, traditional field plotting methods were also conducted within a geographical information system (GIS). Six 0.06 ha plots were re-created in the same locations as the field plots by using ArcGIS Pro to digitise the plot centres that were visible in the orthomosaics. A circular buffer with a radius of 13.82 m was added to each one to create a plot boundary. Each seedling visible within the plot boundary was then manually digitised within the GIS (Figure 2a) and exported as a point data set in shapefile format. The analysis was conducted on both the 0.7 cm and 1 cm datasets, however, the resolution was sufficient to identify all seedlings. The results therefore combine counts for both datasets.

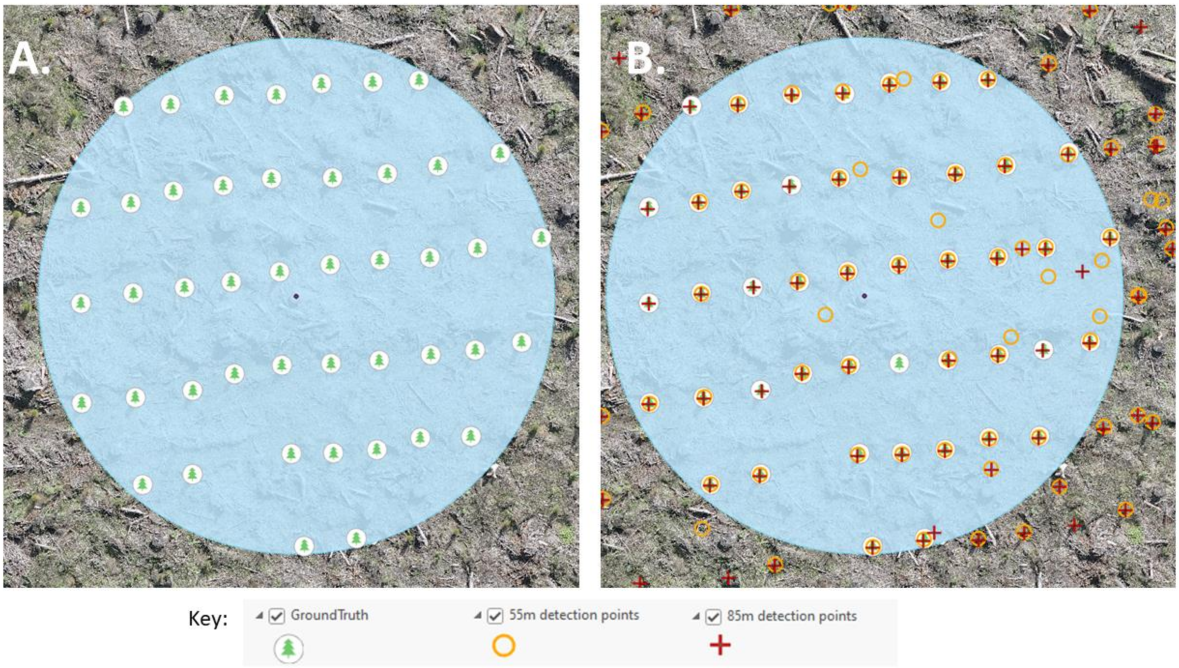

Figure 2. Example plot (blue circle) showing (a) manual annotations of seedlings (green tree symbol) and (b) automatic detection overlaid on a 1 cm orthomosaic. In (b), detections from the 0.7 cm (yellow circles) and 1 cm imagery (red crosses) are shown, demonstrating a higher false positive rate (inaccurately detected as seedlings) for the higher resolution imagery.

Commercial seedling detection

To provide an effective comparison, the spatial layers for the seedling detections were cropped to the same area using the 0.06 ha plots created for the field data and traditional plot method (Figure 2). Accuracy, precision and recall of the seedling detection algorithm were then calculated for both the 0.7 cm and 1 cm dataset. See section 3.6 for a description of the statistical analysis.

Forest density grid

A stocking grid was produced utilising the seedling detections layer from Indufor to enable visualisation of stand density across the site. The initial step was to create a grid with a resolution of 20 x 20 m (0.04 ha) using the Create Fishnet tool in the Geoprocessing Tools of ArcGIS Pro. This was then clipped to the stand boundary, and finally a spatial join was implemented between the seedling detections point data and the grid area, adding a seedling count to each compartment of the grid. This seedling count was then adjusted according to the size of the grid cell to account for cells that were not complete (edge cases). The resulting grid was then colour coded to classify areas according to their stocking. The stocking classifications were split from 0-200, 201-400, 401-600, 601-800 and >801 to enable rapid identification of areas that were planted to specification, or areas that were under- or over-stocked, and to what degree.

Time and cost comparisons

To enable comparison of each method, the time taken to conduct each stage of the manual annotation process was recorded. In addition, an average estimate of time taken to conduct field plots and UAV plots in the field was derived through consultation with the Tools For Foresters committee, which includes foresters, silvicultural contractors and inventory contractors. When comparing the time taken to carry out a survival survey using these various methods, a few averages were input into the calculations. It was assumed an average travel time to and from the site of one hour, and an additional set up/pack down time of 30 minutes for field plotting, and one hour for UAV operations.

For the cost comparisons, the Tools For Foresters committee were once again consulted to give an idea of the average costs of UAV operations and the average costs for plotting. Estimated costs per ha for commercial seedling detection were also provided by Indufor.

Cost comparison between the three methods was complicated due to the different estimates for payment. UAV rates in industry are still generally calculated on a daily rate, whereas seedling detection is costed on a per ha rate, and field plotting is calculated on a per plot basis. In order to standardise this, the three methods were applied to a 24 ha site, representative of the size of stand used in this study. The daily rate for UAV operations was calculated by dividing the daily rate by the approximate number of sites of this size that could be covered in a single eight hour working day, which was deemed to be two to three, depending on altitude of the flight. This was worked out by including an hour of travel to and from the forest, an hour of set up time per site, and using the approximate flight times from this project for a 55 m flight (~2 hours) and an 85 m flight (~1 hour). Additionally, a per ha rate was worked out for the UAV methodology by dividing the cost for the site by 24 (area in ha) and for field plotting by multiplying the rate for a single 0.06 ha plot by 16.7 (the approximate number of plots of that size in 1 ha).

3.6. Statistical analysis

To assess how well the different seedling counting methods worked, three standard metrics, commonly used for detection accuracy were employed: accuracy (I), precision (II), and recall (III). These three metrics are essential as they take into account discrepancies between datasets arising from false or missed detections, which can affect the accuracy of total counts when comparing ground truth with experimental datasets. For example, the total counts could be the same if some other objects were erroneously detected as seedlings (false positives), and actual seedlings were not detected (false negatives).

Accuracy quantifies the percentage of the total seedling detections that were correct. Precision is the proportion of the seedlings that were detected that were actually seedlings. Recall is the proportion of the total number of seedlings in the ground truth data set that were correctly identified by seedling detections. These metrics were calculated using the following equations:

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

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

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

Where:

TP (true positive – correct detection)
A correct detection, also known as a true positive, is defined as a seedling that was present in the ground truth and correctly detected in the UAV data.

FP (false positive – erroneous detection)
An erroneous detection, also known as a false positive, is defined as any detection that is not a seedling, such as a weed or logging debris that was incorrectly identified as a seedling.

FN Missed (false negative):
A missed detection also known as a false negative, is defined as a seedling that was present in the ground truth but not detected in the experimental dataset.

TN (True Negatives; not applicable): These are cases in which the absence of seedling is correctly identified, i.e. a missing seedling was correctly identified. These were not included in the analysis.

4. Results

4.1. Seedling stocking comparison

Results from this study showed that, overall, both manual annotations and automatic detections provided very strong results for detection accuracy (Table 2).

Manual annotations provided better results of accuracy, precision and recall (95%, 96% and 99% respectively) than the best performing automatic detections (79%, 88% and 88% respectively; Table 2).

Between the two resolutions of imagery, both datasets provided the same results for the manual annotation, however, the automatic detections consistently performed better with the 1 cm GSD imagery at the plot level than the 0.7 cm imagery, and overall results being significantly higher for accuracy (79% compared with 63%), precision (88% compared with 76%), and recall (88% compared with 78%; Table 2). Conversely, detections from the 0.7 cm dataset were notably higher than those of the 1 cm dataset with 17,684 compared to 15,710 points.

At the plot level, manual annotation exhibited the narrowest range of accuracy, precision and recall (85-100, 93-100% and 90-100% respectively; Table 2). Automatic detections displayed poorer performance with the 1 cm GSD data exhibiting greater variability in accuracy, precision and recall (64-91%, 74-95% and 72-98% respectively; Table 2). Automatic detections on 0.7 cm GSD dataset demonstrated even greater levels of variability for accuracy, precision and recall (47-80%, 51-94% and 62-91% respectively; Table 2).

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Table 2. Overall accuracy, precision and recall for all plots, ordered by results for accuracy). Results are combined for manual annotation of 0.7 cm and 1 cm GSD imagery as both performed equally in this task.

Method	GSD (cm)	Plot	Accuracy (%)	Precision (%)	Recall (%)
Manual seedling annotation	0.7,1	1	100	100	100
		2	95	100	95
		3	100	100	100
		4	85	93	90
		5	92	100	92
		6	94	100	94
		Overall	95	99	96
Commercial seedling detection (55m)	1	1	62	78	76
		2	80	87	91
		3	67	79	82
		4	47	51	87
		5	51	75	62
		6	69	94	72
		Overall	63	76	78
Commercial seedling detection (85m)	0.7	1	91	93	98
		2	85	89	95
		3	90	92	98
		4	68	74	90
		5	64	85	72
		6	71	95	74
		Overall	79	88	88

4.2. Stocking Density

As the results from the 0.7 cm data set at the plot level, were found to be sub-optimal, stocking density was conducted on the 1 cm GSD data alone.

The stocking grid created in ArcGIS Pro (Figure 3) revealed a wide range of stocking across the stand from 0-975 stems per ha (sph) per grid cell (Table 3). When this is compared to the results from the field plots, it can be observed that the range is a lot greater than that observed by the field plotting (517-783 sph) and for the automatic detections, using the same data as the stocking grids but constrained to the same sample plot areas (550-800 sph; Table 3).

Averaging of the fishnet across the stand showed an overall stocking of 574 sph (Table 3), which is lower than the average derived from the field plots (831 sph) and the average from the automatic detections confined to the plots (681 sph; Table 3).

Table 3. Stocking range per plot and averaged across the stand according to field plots, automatic detections from within the studies plots, and from a stoacking grid across the site.

Method	Stocking range for plots (sph)	Average stocking for stand (sph)
Field plots	517 – 783	683
Automatic detections (plots)	550 – 800	681
Stocking grid	0 – 975	574

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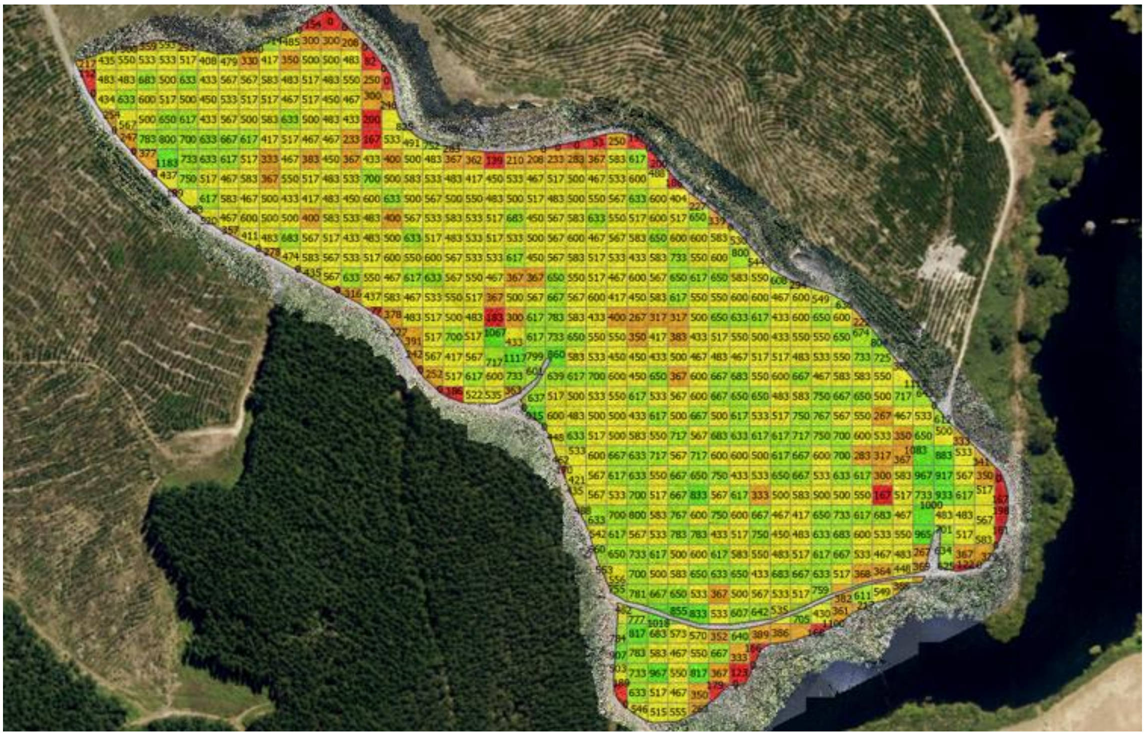

Figure 3. Stocking grid with 0.04 ha cells created from the detection for the 0.7 cm detections. Stocking per cell is indicated in sph, and cells are coloured by sph value in five classes from low (0-200; red) to high (>800; dark green).

4.3. Time comparison

Overall, the three methods had very similar times to carry out assessment of stocking for six plots. Capture of 1 cm GSD UAV data with commercial detection was the fastest (~38 min per plot), followed by UAV capture with manual annotations (~40 min per plot) and manual plotting being the slowest (~55 min per plot). These figures take into account the time taken to set up a photogrammetric dataset to run in the software, however, they don't take into account the length of time that the processing takes. This is because the actual processing doesn't take any manual input required from the operator. Table 4 lists the processing times for each UAV data set for reference.

Table 4. Time comparison of methodologies trialled in this study, including UAV data capture and analysis for different image resolutions, manual annotation, automatic seedling detection and field ploting. Orthomosaic processing times, though provided to give an indication of time required for in-house processing, are ommitted from total time calculations in the final two columns due to their negligible manual input requirements.

<table>
<tr><th>Dataset</th><th>Travel time</th><th>Set up time</th><th>Flight time</th><th>Time to complete 6 plots</th><th>Time to set up processing</th><th>Processing time</th><th>Total time 6 plots (excluding processing time)</th><th>Approx time per plot</th></tr>
<tr><td>0.7 cm UAV (manual)</td><td rowspan="5">01h:00m:00s</td><td rowspan="4">01h:00m:00s</td><td>02h:23m:00s</td><td>00h:12m:30s</td><td rowspan="4">00h:30m:00s</td><td>05h:39m:03s</td><td>05h:05m:30s</td><td>00h:50m:55s</td></tr>
<tr><td>1 cm UAV (manual)</td><td>01h:18m:00s</td><td>00h:12m:30s</td><td>02h:09m:35s</td><td>04h:00m:30s</td><td>00h:40m:05s</td></tr>
<tr><td>0.7 cm UAV (commercial)</td><td>02h:23m:00s</td><td>NA</td><td>05h:39m:03s</td><td>04h:53m:00s</td><td>00h:48m:50s</td></tr>
<tr><td>1 cm UAV (commercial)</td><td>01h:18m:00s</td><td>NA</td><td>02h:09m:35s</td><td>03h:48m:30s</td><td>00h:38m:05s</td></tr>
<tr><td>Field plotting</td><td>00h:30m:00s</td><td>NA</td><td>04h:00m:00s</td><td>NA</td><td>NA</td><td>05h:30m:00s</td><td>00h:55m:00s</td></tr>
</table>

Table 5. Cost study comparing the costs of UAV data capture, commercial seedling detections and field plotting.

Method	Average day rate operations ($)	Average per plot ($)	Cost for a 24 ha site ($)	Average per ha ($)
UAV data capture	1600	NA	533-800	22.2-33.33
Commercial seedling detection	NA	NA	36-52	6-9
Field plotting	NA	27-35	162-210	450.9-584.5

4.4. Cost comparison

For a 24 ha site, the results show that traditional field plotting was the cheapest option ($162-210; Table 5), followed by UAV data capture ($533-800; Table 5) representing approximately a three- to fourfold cost increase. Additional costs of $36-52 are incurred with using the commercial seedling detection services, however, this must be balanced against the time that would be spent by staff manually annotating plots in GIS if done in-house (~10-15 minutes; Table 5).

The scale of the area covered must also be taken into account. Six 0.06 ha plots (UAV or field) at the site would cover an area of 0.36 ha, whereas the commercial detection services would cover the entire 24 ha. When looking at a theoretical cost per ha, UAV plotting works out cheaper at ~$22-33 per ha plus an additional $6-9 per ha for annotation, compared to ~$450-585 per ha for field plotting. Manual annotation of 1 ha would take ~2h47m to 4h10m (based on time taken to do a single 0.06 ha plot multiplied by 16.7), making this exercise unfeasible.

5. Discussion

5.1. Seedling stocking comparison

The first objective of this study was to assess the accuracy of conducting stocking plotting through GIS with field plotting. Overall, the results of this study showed that both manual annotation and automatic detection methods performed very well, with measures of accuracy, precision and recall values of 95%, 96% and 99%, and 79%, 88% and 88% respectively (Table 2). Although more precise, the manual annotations method would not be beneficial for a wall-to-wall assessment due to the amount of manual input required to detect the seedlings. The automatic detections would therefore be more practical, however, these results are a little lower than a previous study that used deep learning to conduct seedling detection on *P. radiata* seedlings, achieving high levels of precision and recall (99.4% and 97% respectively; Pearse et al. (2020)).

Although manual annotation performed better than automatic detections, automatic detections were still capable of strong results. It was notable, however, that the detection model performed better on the 1 cm imagery than on the 0.7 cm data. This is likely due to the additional detail in the 0.7 cm imagery. Deep learning models can perform very well on data that they have been trained on, however, if they have not been exposed to much imagery of a specific resolution or in a specific lighting or with differing site conditions, then performance can drop. Training the model with additional 0.7 cm data could improve results in this regard, however, from an operational perspective, getting this higher resolution almost doubled the data capture time (Table 4), and increased the size of the data, therefore, there would be little benefit in doing this.

The results of the automatic detections were also notably plot-specific. The plots in which the model performed worst were plots 4 and 5, which were notable for their high FP rate and high FN rate respectively. On assessment of the imagery, Plot 4 had noticeably more small clusters of weeds, which could have triggered more erroneous detections (Figure 4). To reduce FPs, models can be re-trained using "hard negative mining" to teach the model where it is going wrong, for example, feeding it examples of erroneously detected gorse or logging debris.

Figure 4. Examples of FPs (white boxes) in plot 4. Detections are represented by yellow circles (0.7 cm data) and red crosses (1 cm data).

A number of the FNs, or missed detections, in Plot 5 were of dead seedlings (Figure 5). This points to a lack of training data for these specific cases. Deep learning algorithms can be highly site-specific and results can be improved by providing additional training data. To help reduce FNs, feeding the model additional training data for things that it missed, for example dead seedlings, will reduce false negatives associated with dead trees. An alternate approach could be to train an additional class, i.e. for dead seedlings, so that the trees are detected and can easily be filtered to show where mortality occurs across the site. As the deep learning models assessed in this study were commercial, these options would need to be discussed with the service provider who could inform on how best to improve results.

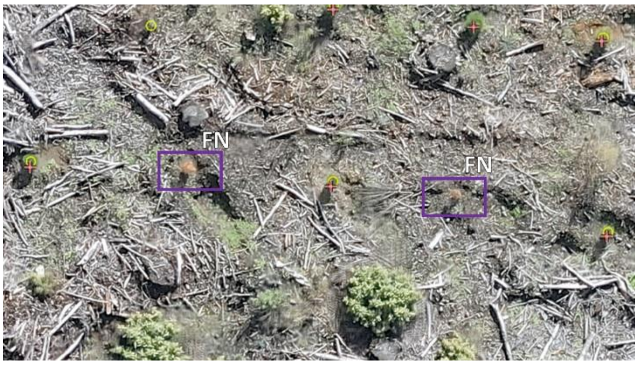

Figure 5. Examples of FNs (purple boxes) in plot 4. Detections are represented by yellow circles (0.7 cm data) and red crosses (1 cm data).

5.2. Stocking density

When comparing the number of detections, the 0.7 cm dataset yielded significantly more detections than the 1 cm dataset. At a glance, the most common difference was that there were more erroneous detections (FPs) with the 0.7 cm dataset, especially around the site boundaries and areas of heavy logging debris. Further analysis revealed that the 0.7 cm dataset contained more erroneously detected weeds as seedlings more often than the 1 cm. A factor could be that the lower the flight altitude, the higher the resolution, resulting in a much more sensitive detection algorithm.

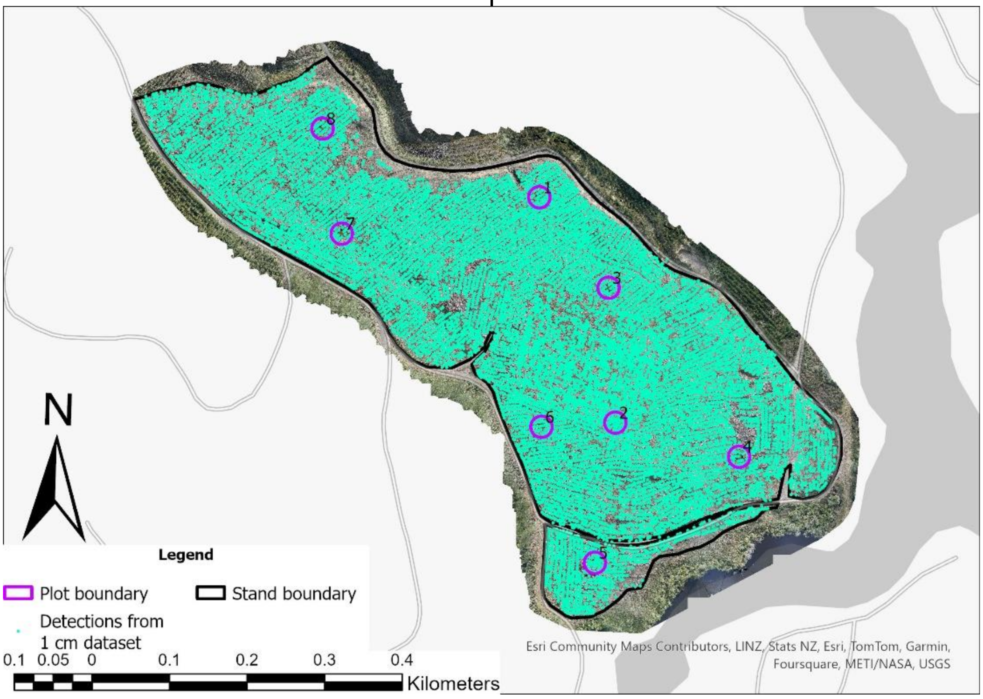

Figure 6. Location of plots (purple circles) and distribution of seedling detections (teal dots) across the site.

No significant difference was observed between the results of the stocking density from field plots and the density derived from the automatic detections from the 1 cm imagery within the same plot boundaries. This demonstrates that although the automatic detections were less accurate than field methods in detecting trees (Table 2), they gave a comparable result when predicting average stocking across the site. However, the field and UAV-based plotting methods both notably overestimated the average stocking across the site when compared with the stocking grid (Table 3). Looking at the range of stocking per plot/grid, it is apparent that the plot-based methods are missing areas of low stocking (Table 3 and Figure 6).
Some of these grids may correspond to unplantable areas with heavy logging debris, such as old skid sites, highlighting the utility of this methodology for improving mapping of net stocked area. Other areas with low detections could be due to mortality or missed planting, in which case this information would be useful for the forester to plan early intervention operations. Equally, overstocked areas need attention and could be identified on a map for closer inspection. The creation of a colour coded stocking density grid acts as a useful visual aid for identifying areas that require attention (Figure 3), enabling foresters to target issues and note opportunities for intervention.

5.3. Cost benefit analysis

Typically, the quality of data is only measured through its precision and accuracy, however, a contemporary view is that the quality of data should also be measured in terms of benefits obtainable from the data (Kangas et al., 2018).

The time comparison study for plotting indicates that the quickest method was the UAV plotting with commercial seedling detections. Although being more than one third quicker per plot, this time study did not take into account that stocking could be assessed over the entire site for the same amount of time and cost as simply assessing the plots, representing a significant increase in the amount of information available to the forester.

Regarding the cost, to carry out a standard survival assessment at a 24 ha site, putting in six field plots would be significantly cheaper than capturing UAV data ($162-210 compared to $288-$360). Although not practical to conduct a wall-to-wall assessment using field methods, when the two methods are compared on a per ha basis, the UAV data capture is considerably cheaper at ~$22-33 per ha, compared to ~$451-$585 per ha. Since travel is a big cost factor, it is also notable that multiple 24 ha areas could be completed in a single day using UAV methods, however, the field plotting is time-consuming and so potentially only 10-12 plots per day could be assessed, incurring additional travel costs to cover the same number of sites over multiple days.

Although the evaluated wall-to-wall method is quicker than field plotting, and can cover the entire site in less time, the method is still less accurate than field based plotting. As discussed previously, improvements to the deep learning model could help to bridge this gap, however, at this stage stocking is the only thing being assessed. With more work, additional aspects, such as health assessments, weed growth or mortality surveys, could be incorporated into the wall-to-wall methodology, increasing the advantages over current field plotting methods.

The wall-to-wall site capture method and commercial seedling detections, as demonstrated in this study, are best suited for foresters working with medium to large stands. This approach enables rapid coverage of extensive areas and provides a comprehensive overview of the forest's condition, including stocking and inferring survival.

6. Conclusion

This study has indicated that stocking detection from UAV data can be conducted with a high level of accuracy, precision and recall. Though not as accurate as field plotting at the individual tree level, the real advantage of the wall-to-wall method lies in the ability to assess stocking at the stand level, rather than at the plot level. This study has demonstrated that there can be such a thing as having too much resolution, finding that the lower resolution imagery (1 cm GSD) provided the best detections, and also efficiencies in data capture and cost. In addition, some shortcomings of the deep learning approach were identified, and discussed along with possible mechanisms for improvement. It is anticipated that through these improvements, the accuracy of the detections would increase to be more in line with those observed in the literature.

This study also demonstrated that the value of wall-to-wall capture extends beyond just the accuracy and precision of the detections. Instead, the value is more evident through the supplementary benefits, capabilities, and possibilities it offers. The detailed information that the forester can aggregate from the wall-to-wall methodology could aid in decision making especially in the early stages of the stand, providing an opportunity to resolve issues promptly and reduce forest management costs at a later stage. By embracing the potential of UAV technology and thoughtful data analysis, foresters can improve their forest management practices and make more informed decisions for the sustainable future of our forests.

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