Enhancing Seedling Detection in New Zealand Forestry

A Multi-Datastream Approach

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Supervisors

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01 Background

Establishment phase

- Substantial costs with no immediate economic benefits
    - *Pinus radiata*:$1100-1600/ha
    - *Pseudotuga menziesii*: $1800-2300/ha

(depending on stocking)

Health and stocking assessment

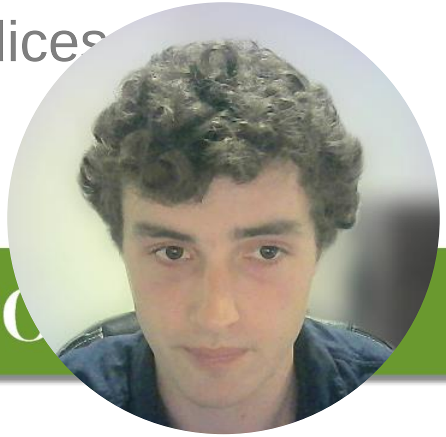
- Informed forest management decisions
- Nurseries insights into seedling performance

Ground methods can be diffic
best of times

01 Background

Seedling detection studies

- UAVs provide a **cost-effective and efficient alternative** to conventional ground-based surveying methods (Feduck et al., 2018)
- Combining high-resolution full-colour (red/green/blue, RGB) imagery with deep learning algorithms allows for the **accurate detection of seedlings** (Pearse et al., 2020)
- While multispectral cameras **detected more seedlings** than RGB cameras, they also had **increased erroneous detections** (Singleton et al., 2024)
- **Potential for accurate health classification** of seedlings using spectral indices with machine learning (Singleton et al., 2024)



01 Background

The DJI Mavic 3 Enterprise Multispectral UAV

- Significantly longer flights times
- User friendly
- Replacing the DJI Phantom 4 series as the industry standard UAV
- Can capture high-resolution RGB and multispectral Imagery **simultaneously**

02 Research objectives

Overall objective: **Improve seedling detection in plantations through integrating high-resolution RGB and multispectral UAV imagery for multimodal deep learning**

Research Question 1: **How does input imagery affect model accuracy? (RGB vs MS vs Combined)**

Research Question 2: **How does the health status of seedlings impact model accuracy?**

Research Question 3: **How accurately can we make detections for *Pseudotsuga menziesii*?**

03 Methodology

UAV imagery collection

DJI Mavic 3 Enterprise Multispectral

- 65m above surface level (ASL)
- 85% forward and side overlap of images
- 15m/s horizontal flight speed
- Operational spec

GNSS location collection

Trimble Geo 7X differential GNSS receiver

- 2m receiver pole
- 15cm locational precision
- Regions where detection is expected to be difficult
- Record the health status of seedlings

03 Methodology

Seedling health status classification

- Vigorous: Notable growth
- Alive: Little to no growth
- Dying: Visible decline
- Dead: Extreme decline (clear red needles)

Vigorous

Alive

Dying

Dead

03 Methodology

High resolution

Red, Green Blue (RGB)

Multispectral

Red (R)
650 ± 16 nm

Green (G)
560 ± 16 nm

Red edge (RE)
730 ± 16 nm

Near infrared(NIR)
860 ± 26 nm

03 Methodology

Model generation

- 1,577 ground truth seedlings
- 25,079 desk annotated seedlings (13,969 *Pinus radiata*, 11,110 *Pseudotsuga menziesii*)
- 70% of annotated seedlings for model training
- 30% for model validation

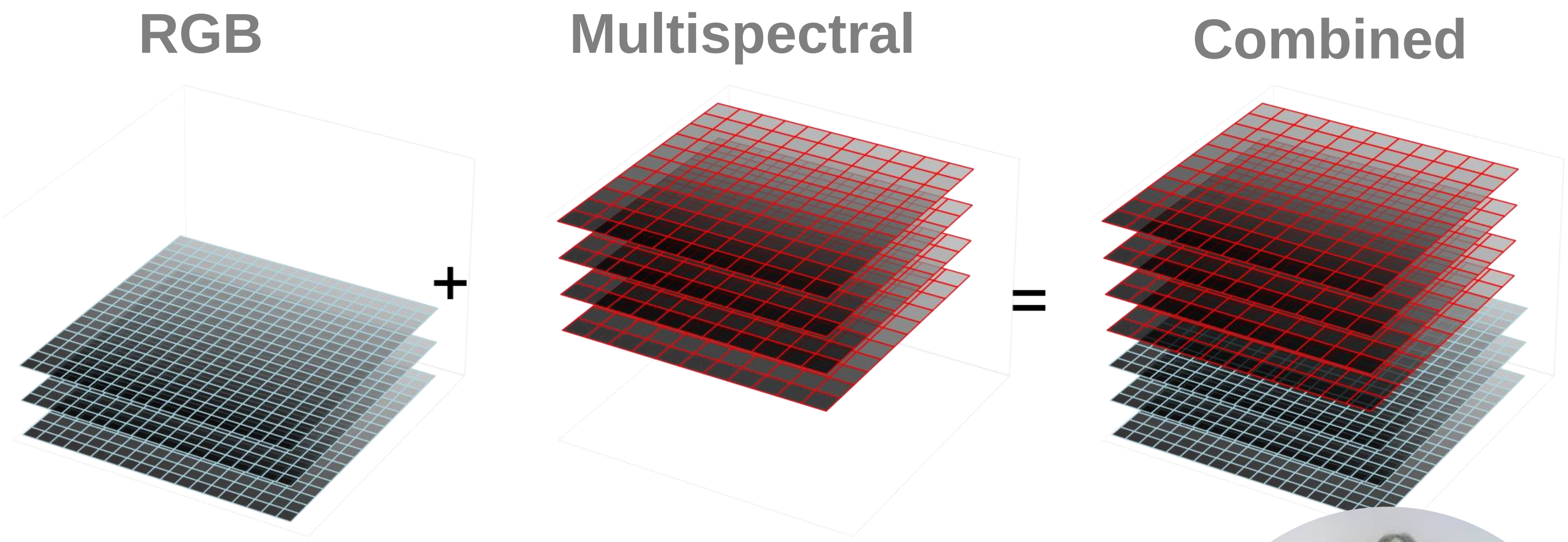
Model	Inputs
RGB	**RGB imagery** GNSS located seedlings Annotated seedlings
Multispectral	**Multispectral imagery** GNSS located seedlings Annotated seedlings
Combined	**RGB imagery** **Multispectral imagery** GNSS located s[illegible] Annotated [illegible]

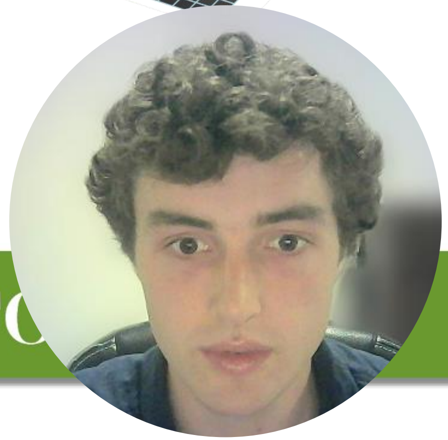
Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks
https://doi.org/10.48550/arXiv.1506.01497

03 Methodology

Model

- Faster-RCNN model
- Used successfully in New Zealand plantation forestry
- Modified to include 4 & 7 input channels for multispectral, and combined models in the initial convolutional layer

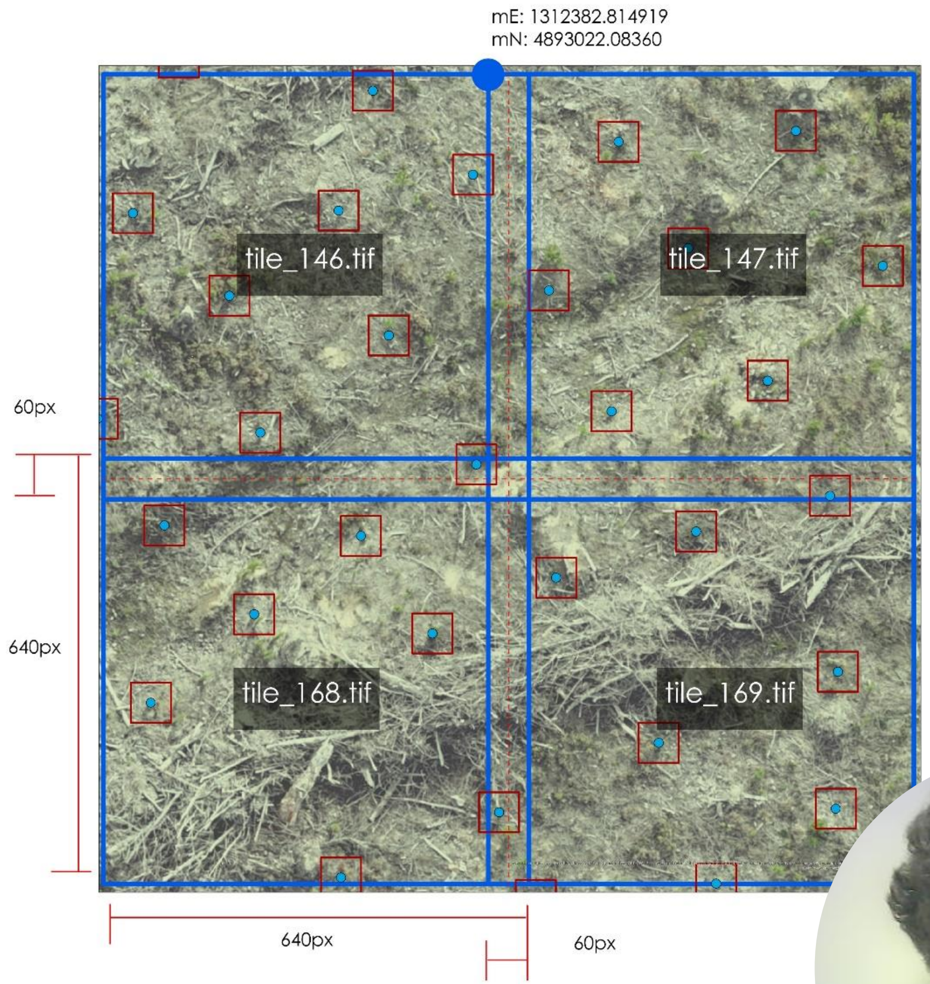




03 Methodology

Preparing dataset for deep learning

- 640 x 640 pixel images
- ½ m overlap
- Fixed size 1m bounding box
- Record the NZTM2000 coordinates of top left corner of each image tile



03 Methodology

Model evaluation

- A detection is considered correct (TP) if it is within 30 cm of the actual seedling location
- **True Positives (TP):** Correctly detected seedlings
- **False Positives (FP):** Incorrectly detected seedlings
- **False Negatives (FN):** Missed detections of actual seedlings
- **Location offset:** the distance between the predicted bounding box centroid and the ground truth

$$Accuracy = \frac{TP}{TP + FP + FN}$$

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

$$Recall\ (Sensitivity) = \frac{TP}{TP + FN}$$

$$F1\ Score = \frac{2 \times Precision \ldots}{Precision \ldots}$$

04 Study area

Blue Mountains, Otago, New Zealand

	Pinus radiata				*Pseudotsuga menziesii*
Site Number	1	2	3	4	5
					
Site area (ha)	27.5	16.5	17.5	35.7	46.6
Annotated seedlings	2,625	2,999	3,392	3,341	11,110
GNSS locations	287	250	303	292	445
Multispectral GSD (cm/px)	2.56	2.78	2.83	2.56	2.52
RGB GSD (cm/px)	1.50	1.63	1.66	1.50	1.49
Vegetation	Minimal	Minimal	Moderate	Moderate	
Elevation range (m ASL)	284-355	167-277	169-238	86-222	

05 Results

Overall performance

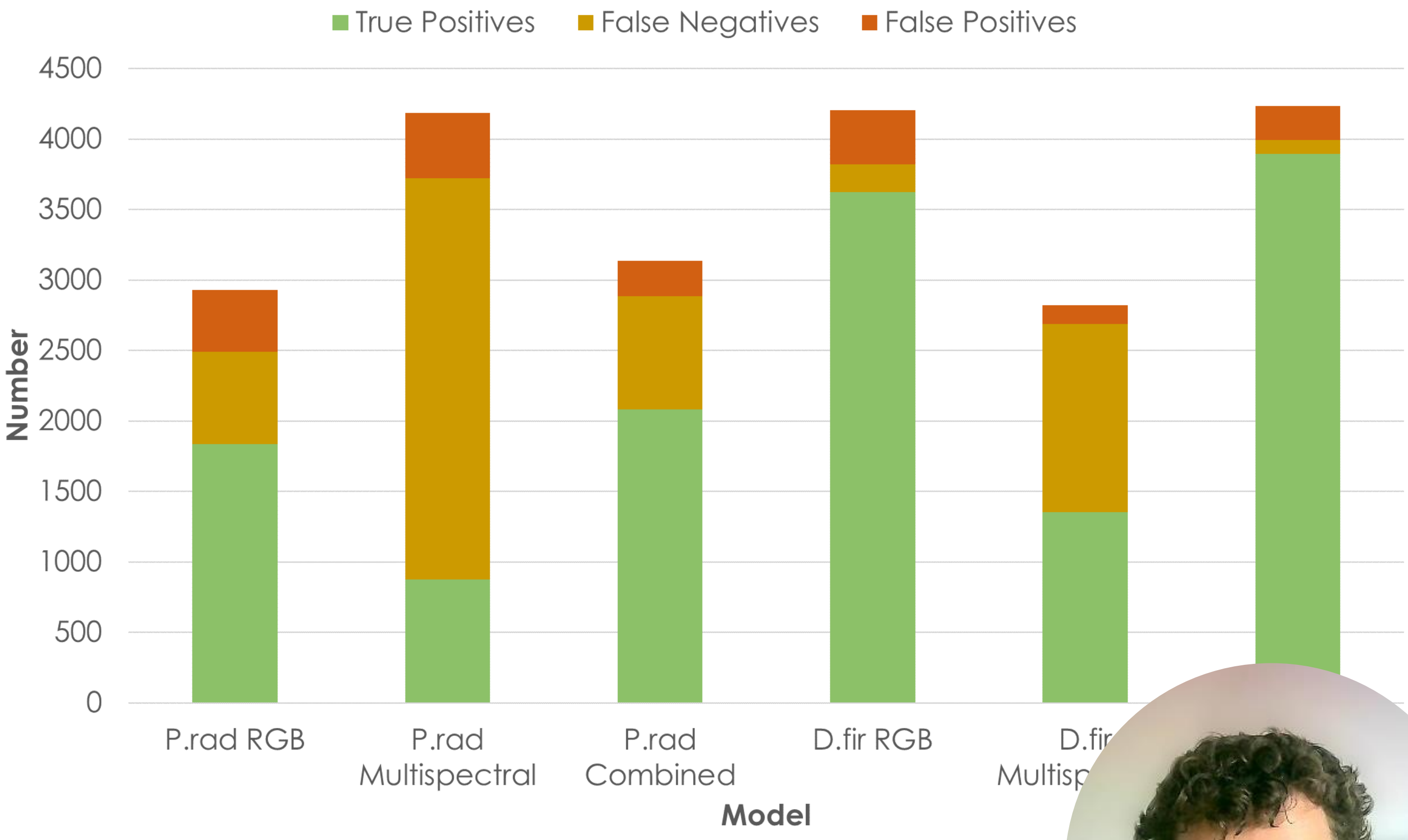
- Combined models performed better than RGB and Multispectral models
- RGB models outperformed Multispectral models
- A high degree of accuracy was achieved across *Pseudotsuga menziesii* models

Species	*Pinus radiata (P.rad)*			*Pseudotsuga menziesii (D.fir)*		
Model	**RGB**	**Multispectral**	**Combined**	**RGB**	**Multispectral**	**Combined**
Precision	80.6%	65.5%	89.1%	90.4%	90.9%	94.2%
Recall	73.7%	23.6%	72.1%	94.9%	50.4%	97.5%
F1 Score	77.0%	34.7%	79.7%	92.6%	64.8%	95.8%
Accuracy	80.6%	65.5%	89.1%	90.4%	90.9%	94.2%

05 Results

Overall performance

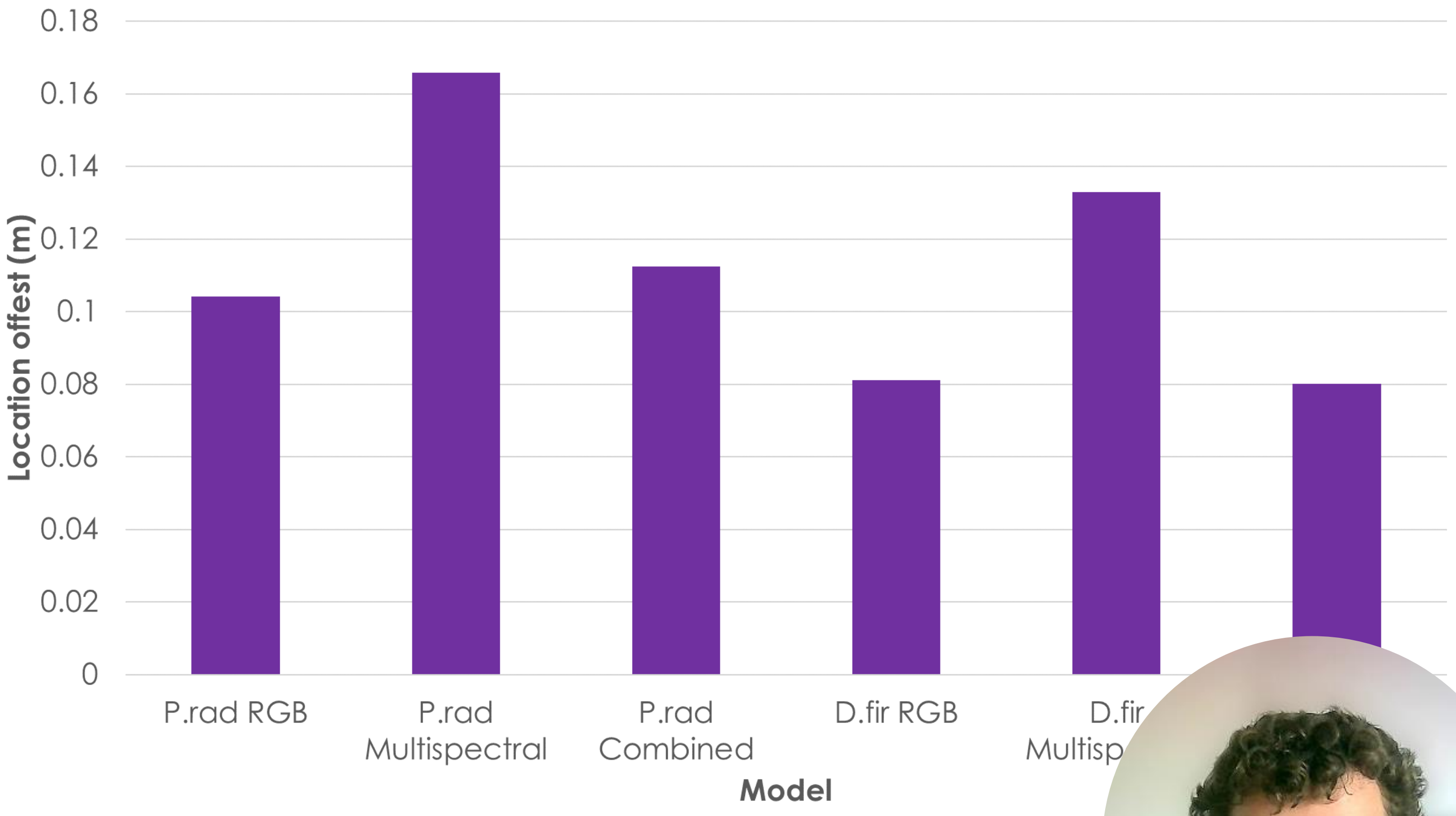
- Combined models performed similar to RGB models
- Multispectral models produced a higher number of false negatives



05 Results

Location offset performance

- Minimal improvement in location offset was achieved for combined models
- Multispectral models had a higher average location offset



05 Results

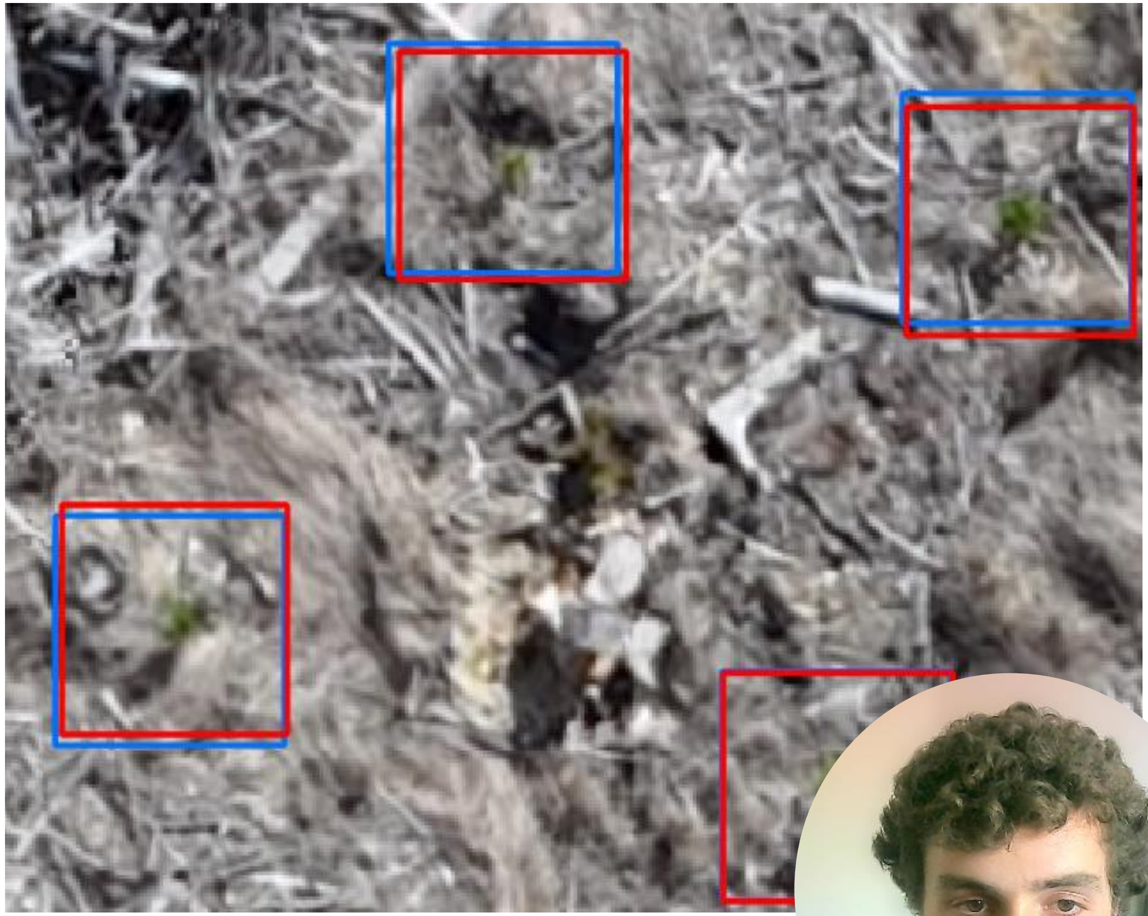
Impact of seedling health

- Less healthy seedlings are more difficult to detect

*NB: Due to class imbalance **not** conducted for Pseudotsuga menziesii*

04 Results

RGB vs Combined



UC FO

06 Conclusions

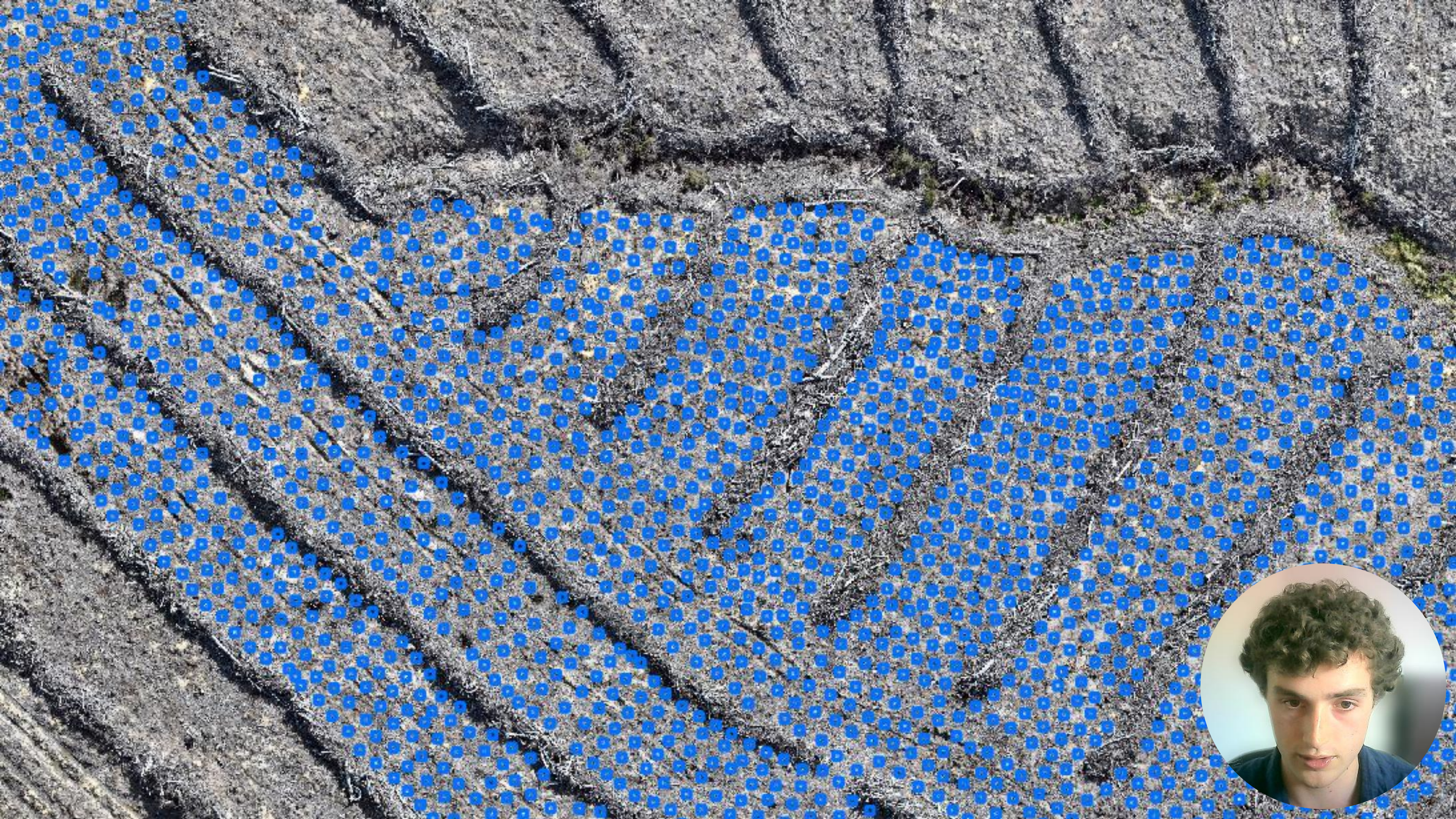
Take-aways

- Integrating RGB and Multispectral imagery improved model performance

- Developed the first *Pseudotsuga menziesii* seedling detection model for New Zealand plantation forestry

- Multispectral models performed worse than RGB models

- Less healthy *Pinus radiata* seedlings are more difficult to detect for all tested



07 Next steps

Current work

- Integrating machine learning to distinguish between health classes of detected seedlings using a Random Forest Classifier

Future work

- Applying at an operational level with Ernslaw One Ltd
- Determining decision thresholds
- Impacts of time of year
- Automated UAV spot spraying

08 Acknowledgements

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