SCION
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Industry applications of UAVs

Grant Pearse

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FOREST GROWERS RESEARCH

Where do UAVs fit into forestry?

UAVs: rapid technological change
- Lots of attention
- But what is possible?

- Project trialled UAVs for forestry:
  - Roles and cost efficacy
  - Detect wind damage
  - Carry out cutover mapping
  - Assess post-planting survival
  - Assess post-harvest waste

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Where do UAVs fit into forestry remote sensing

UAV	Aircraft	Satellite
Small areas (<10 km^2)	Medium to large areas	Large areas
Very high resolution (1 cm)	High-resolution (30 cm)	High costs for < 1 m resolution
Flexible sensors	Only source of LiDAR	Stereo images (point clouds)
Fast deployment, data availability	Costs reduced for large areas	Dedicated tasking
Commercial providers \$3-25/ha (\$20-50/ha with ground survey)	LiDAR (\$2-20/ha) depending on area	As low as \$1.50 / km^2 (5-m RapidEye)
Reliability, processing costs	Uneconomical for small areas	Cloud cover, large minimum areas

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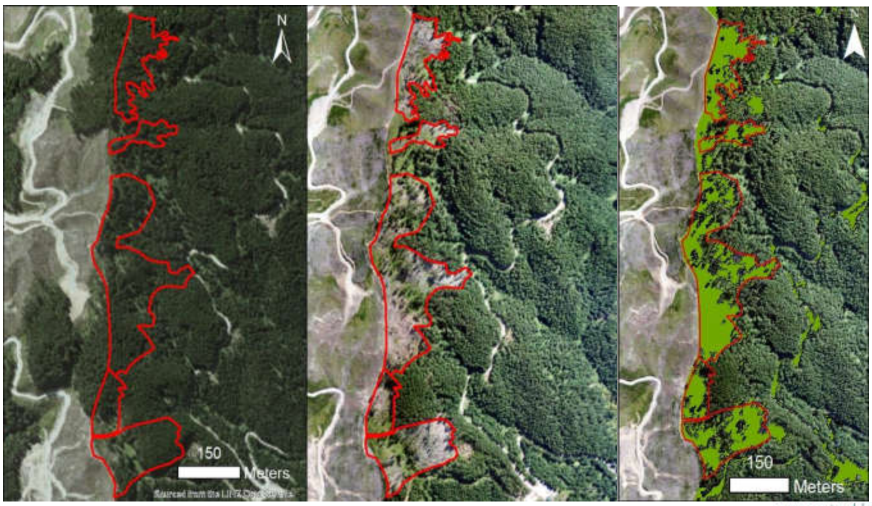
UAV mapping of wind damage



- RGB imagery from a fixed-wing UAV
- Higher resolution imagery from multirotor
- Affected area, value recovery

- Simple classification (Mahalanobis + Max Likelihood – ArcGIS)
- 9 ha mapped cf. 10.8 ha classified
- Robust, fine-scale results

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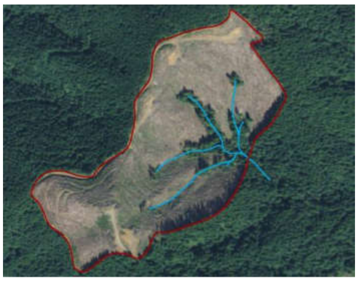
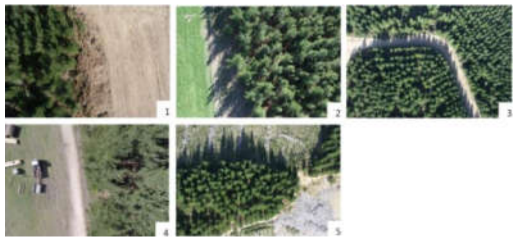
Automated UAV mapping of cutover





Examples of imagery used to train support vector machine classifier

- Collaboration with University of Canterbury
  - David Hunt - ME thesis
- Design and build a custom UAV
  - Edge detection and tracking

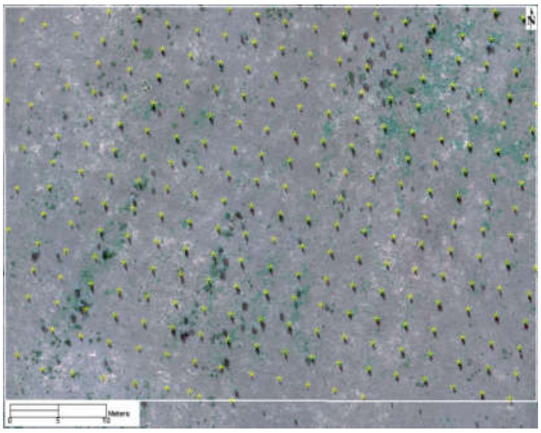
Capture video of forest canopy → Classify images in real-time → Find and smooth edge → Adjust flight path to follow edge

Automated cutover mapping

- Accurate classification from RGB
  - SVM: 90%
  - Colour-based: 83%
- Mean deviation from edge:
  - 2.4 m (before smoothing)
- UAV successfully identified and tracked edge
- Methods also applicable to static RGB imagery

Examples of imagery used to train support vector machine classifier

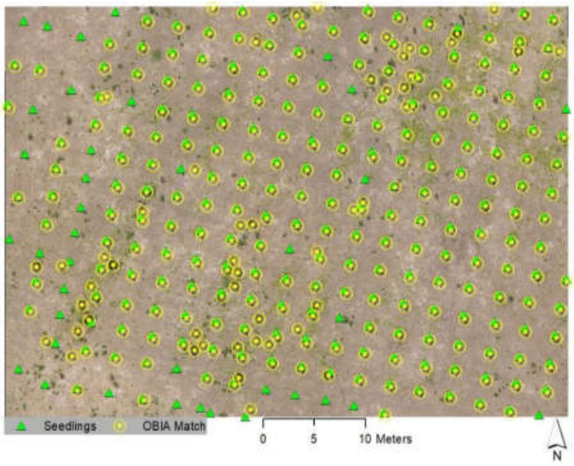
Post-planting assessment: 8-months



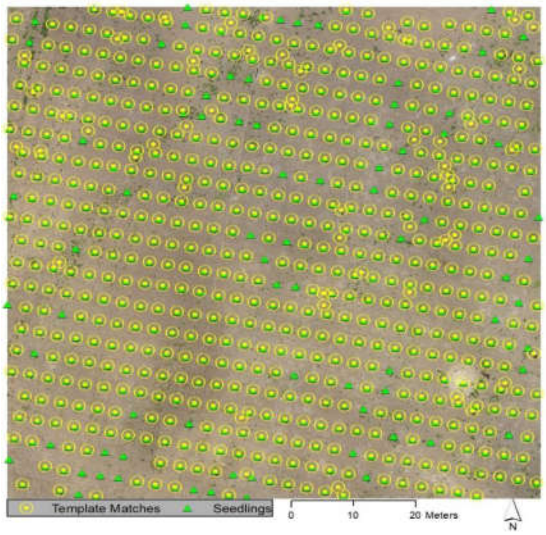
- Density, survival, weed infestation
- Large training area + large validation area
- Manual counts and mortality assessment

- Object-based image analysis
  - ‘rules’ defining a healthy seedling
- Cross-correlation template matching
  - 90 samples (‘training images’)

Post-planting assessment - results

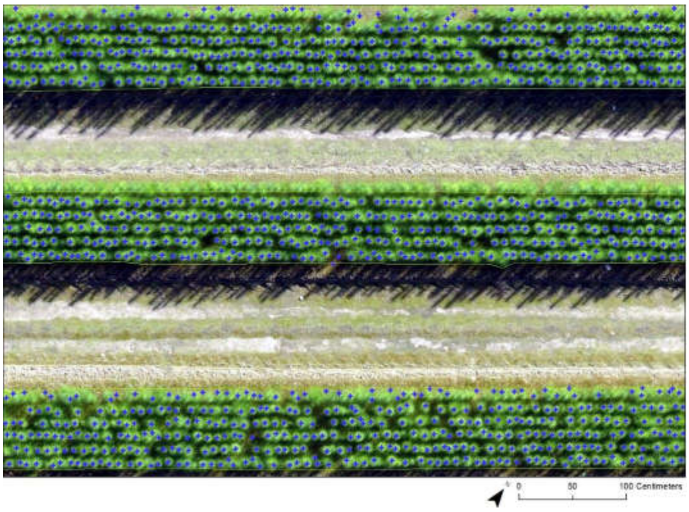


- OBIA precision of 83% and sensitivity of 86%
- False positives from weeds
- Excluded dead seedlings (desiccated)



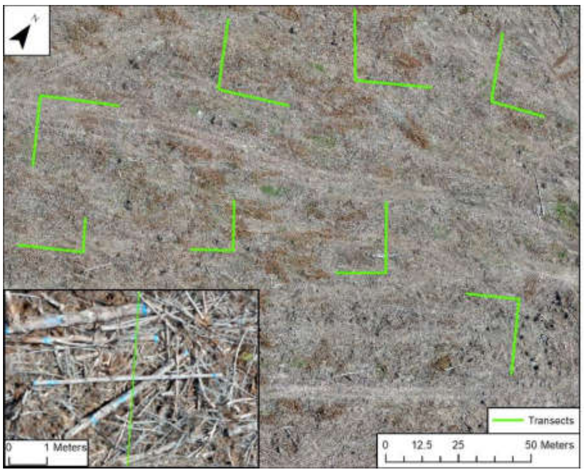
- Template: precision of 92% sensitivity of 89%

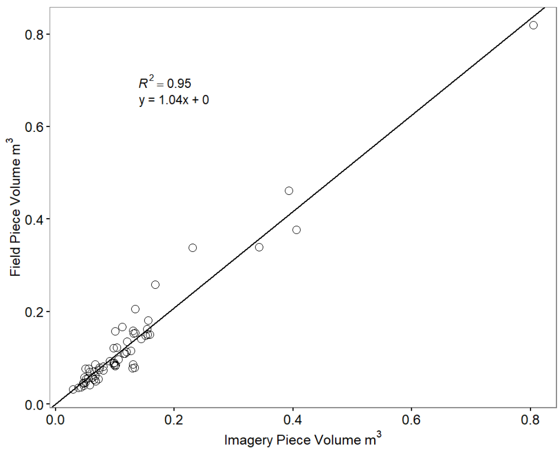
Correlation templates for forestry



- Seedling counts: 90% accuracy
- Matlab, eCognition, OpenCV, SciLab

Post-harvest Wagner waste from a UAV





- Field: 85.6 m^3 cf. Imagery: 84.4 m^3
- Missed rot, but orientation and transect arrangement favour imagery

Conclusion

- Project validated several new applications for UAVs
  - Established advantages and disadvantages
- Highlighted most promising applications for future research
- Focused on accessible data: RGB from < 5K UAV
- Used readily available tools where possible – ArcGIS, QGIS
  - Cross-correlation templates available in OpenCV, SciLab
- Details and methods available in technical note and full report

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