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GEOSPATIAL WORLD FORUM

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Tracking New Zealand's changing carbon landscape using advanced geospatial techniques

Laise Harris

Informatics, Manaaki Whenua – Landcare Research, Palmerston North





What Manaaki Whenua – Landcare Research do is focussed around:

Four ambitions for New Zealand



OUR ENVIRONMENT

We are an environmentally informed nation, taking action together.



OUR BIODIVERSITY

We know, value and actively preserve our unique biota and ecosystems.



OUR BIOSECURITY

Our land is protected from invasive biological threats.



OUR LAND

We use our land, soil and water resources wisely.



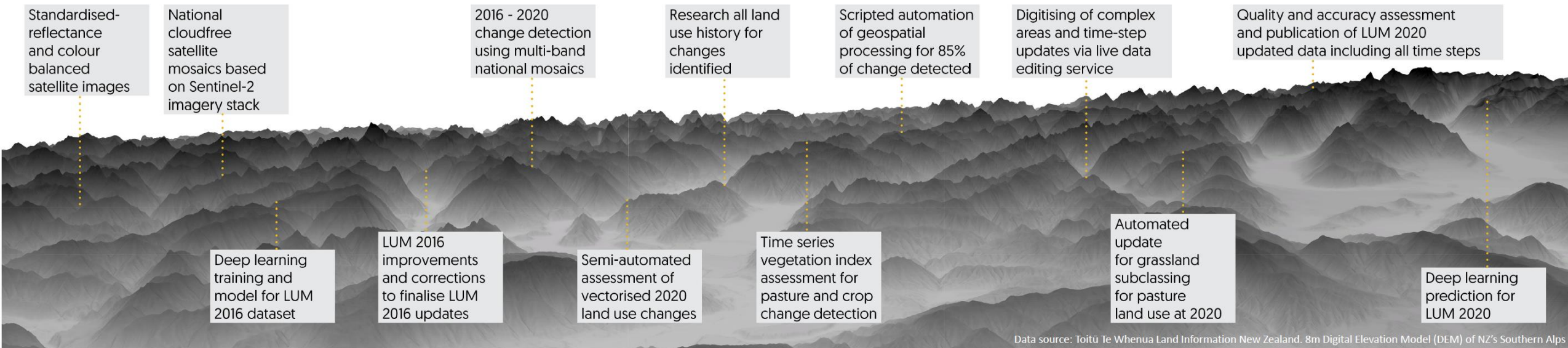


Manaaki Whenua
Landcare Research



Land Use Carbon Analysis System (LUCAS) Land Use Map (LUM) 2020

LUCAS LUM 2020 processing stages



Manaaki Whenua – Landcare Research team: Laise Harris (project coordination and geospatial), James Shepherd (remote sensing), David Pairman (automation and geospatial coding), Brent Martin (deep learning/AI), Stella Beliss, Anne Sutherland, Graeme Curwen, James Ardo, Christine Martelletti and Simon Planzer.
Under contract from New Zealand's Ministry for the Environment.

Winner: 2023 New Zealand Science Award for Team, awarded at Parliament in December 2023.

Six major stages of data processing in LUM 2020:

- Seamless cloudfree satellite mosaics
- Detecting forest change
- Detecting non-forest change
- Scripted automation of geospatial processing and integration of spatial features and attribute tabular updates
- Digitising using ArcSDE feature service
- Deep learning model, training and predictions



Major achievements:

In LUM 2016, ~6,000 change polygons were captured, affecting ~30,000 LUM areas

In LUM 2020, ~**30,000** change polygons were included, affecting ~190,000 LUM areas

LUM 2020 took 12 months to complete (start to end).

New techniques include:

- Deep learning trial
- Rapid triage to code data
- NDVI temporal analysis
- Automated 'burns' (80%)
- Editing in web-service
- New IDA process (raster)

1. Creating seamless national mosaics with Sentinel-2 satellite imagery

Imagery acquired over summer was collated, atmospherically and spectrally corrected and colour-balanced for analysis. Standardised reflectance techniques were used to remove cloud, haze and cloud shadow (Figure 3). The resulting cloud-minimised patches of imagery were used to produce national cloud-free mosaics with visible topography, maintaining shade and hill effects. Imagery was then spectrally "flattened" to remove the effects of sun and view angle, and hill shading (Figure 4). This created a consistent series of analysis-ready, seamless annual national mosaics (Figure 5). These are used to compare land at different dates.

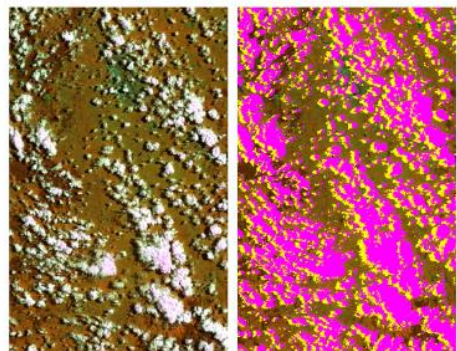


Figure 3 Cloud removal

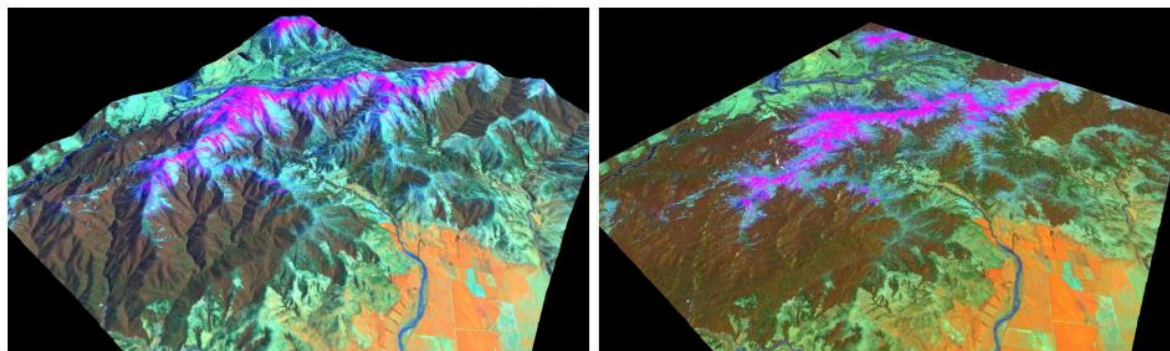


Figure 4 Correction of topographic effect and reflectance variance

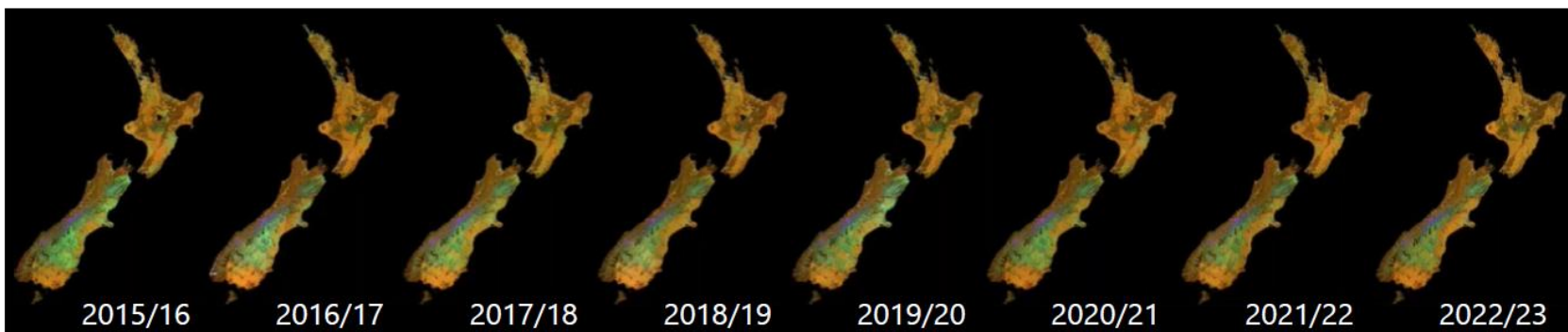


Figure 5 NZ's seamless national mosaics with Sentinel-2 satellite imagery from 2015/2016 to 2022/2023



Seamless cloudfree Sentinel-2 satellite mosaics are corrected for:

- Atmosphere effects
- Spectral variance
- Colour-balanced
- Remove cloud and haze
- Spectral flattening

These mosaics form the basis of all our national land-based change datasets (12+ published journals by MWLR)



Article

Automated Mosaicking of Sentinel-2 Satellite Imagery

James D. Shepherd ^{1*}, Jan Schindler ² and John R. Dymond ¹

2. Detecting forest change between 2017 and 2020

Difference detection techniques, including advance segmentation using iterative elimination (Figure 6), assess land use change and forest loss that occurred between 2017 and 2020.

Semi-automated techniques were used to remove false positives and ensure that a land use change had occurred.

Non-anthropogenic land use change was identified.

The resulting data was prepared for use in scripted automation techniques.

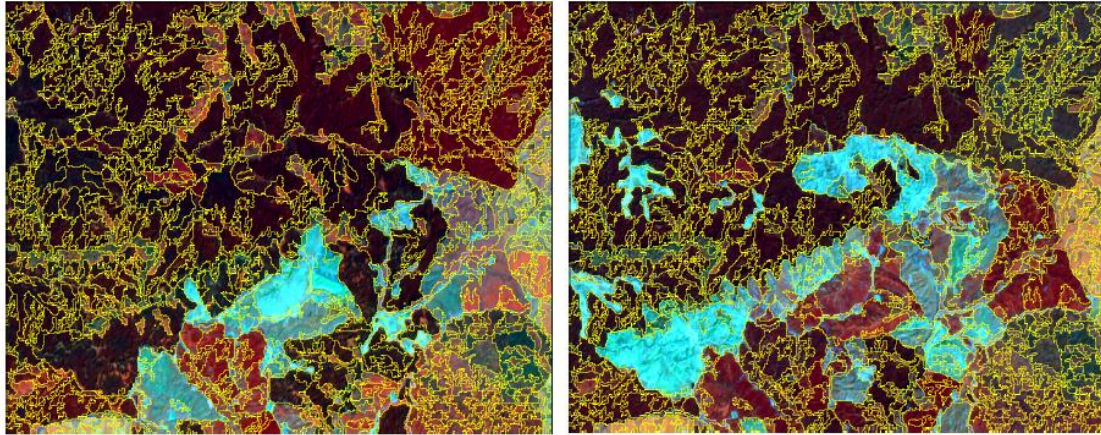


Figure 6 Iterative elimination segmentation

3. Detecting non-forest change (shrub, grass, crop, wetlands, water and settlements)

Different change detection rules were applied to each non-forest class of LUM using a combination of computational analysis, ancillary datasets and Synthetic Aperture Radar (SAR).

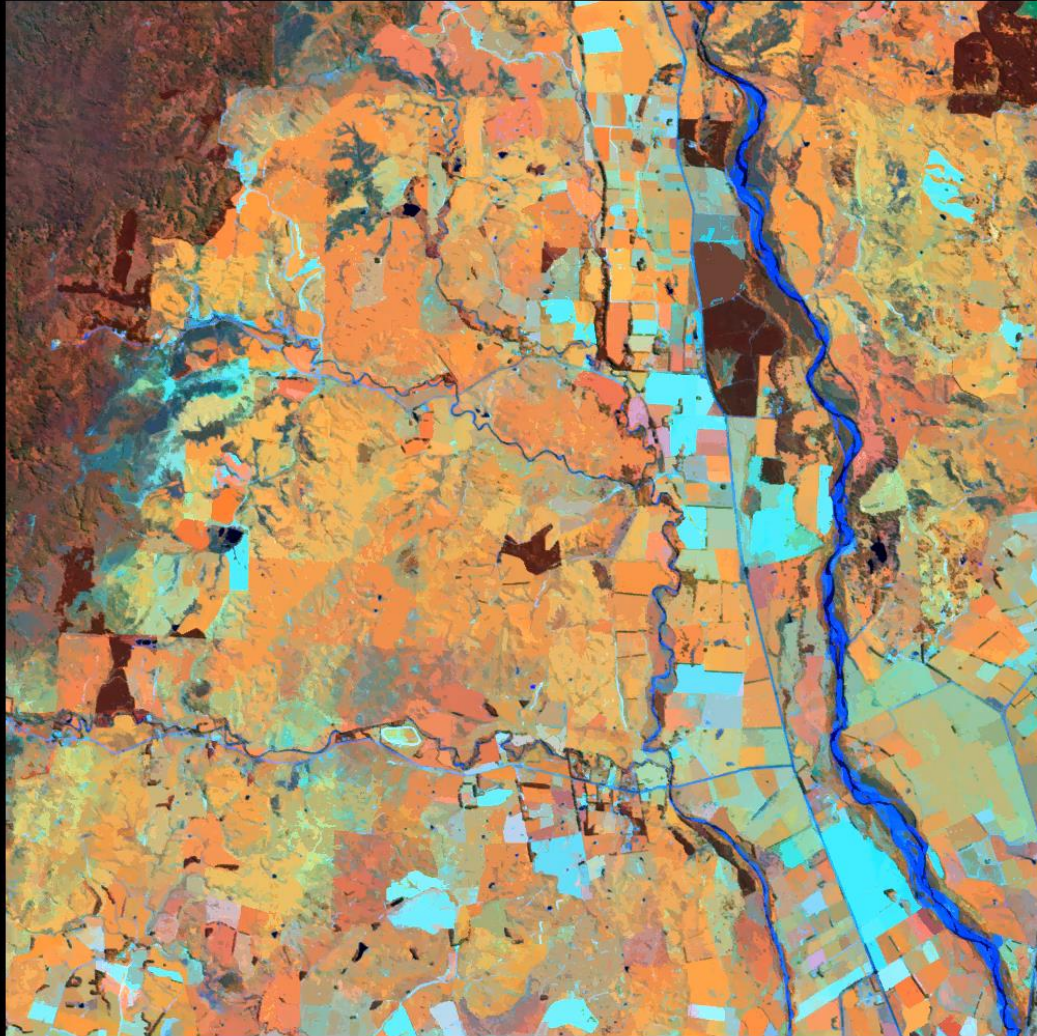
- Natural and man-made open-water was identified using imagery combined with SAR.
- An update of wetlands from NZ's Land Cover Database v5 (LCDB 5) was incorporated.
- Cropland change was identified using temporal sequence analysis of cultivation events.
- Areas of change were manually screened to ensure that a land use change had occurred.
- Different subclasses were assigned, including species or type of class change.
- Grassland was subclassified into grazing type (dairy and non-dairy) or ungrazed.

Detecting forest and non-forest change:

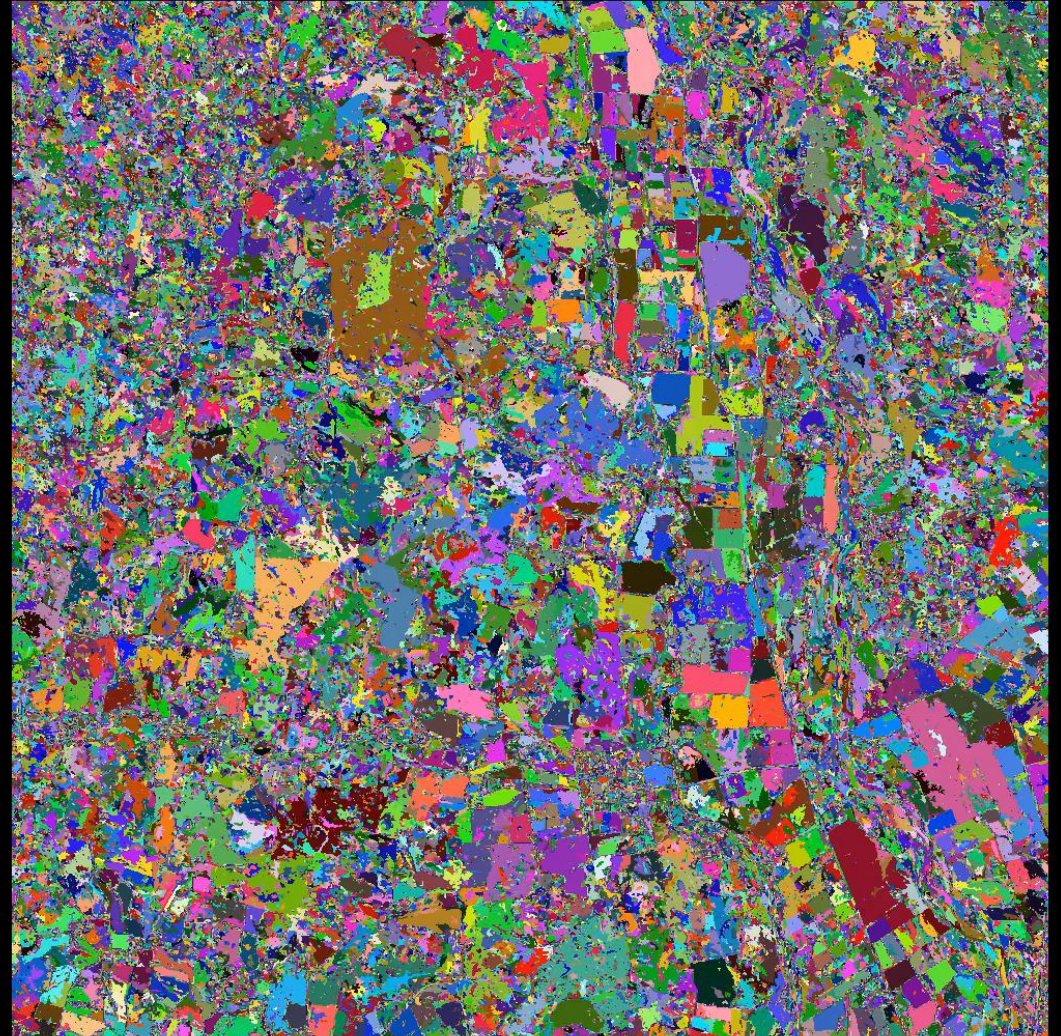
- Difference detection between nominal dates
- Advanced segmentation and iterative elimination (GEOBIA process)
- MapAccuracy visual assessments and triage (validate, separate into draw or burn, classify)
- Water uses SAR (Radar)
- Wetlands from LCDB 5
- Cropland using temporal NDVI sequence analysis
- Grassland using new IDA

Article
**Operational Large-Scale Segmentation of Imagery
Based on Iterative Elimination**

James D. Shepherd ^{1,*}, Pete Bunting ² and John R. Dymond ¹



2012



176086

Example of 'burning' LCDB vegetated wetland polygon

New red polygon burns over underlying LUM boundaries

Remaining slivers which are defined in a variety of ways (or combinations of ways) i.e. size, shape, proportion, class..

Control over general 'longest boundary approach' so consider new boundary as authoritative (unless its not!)

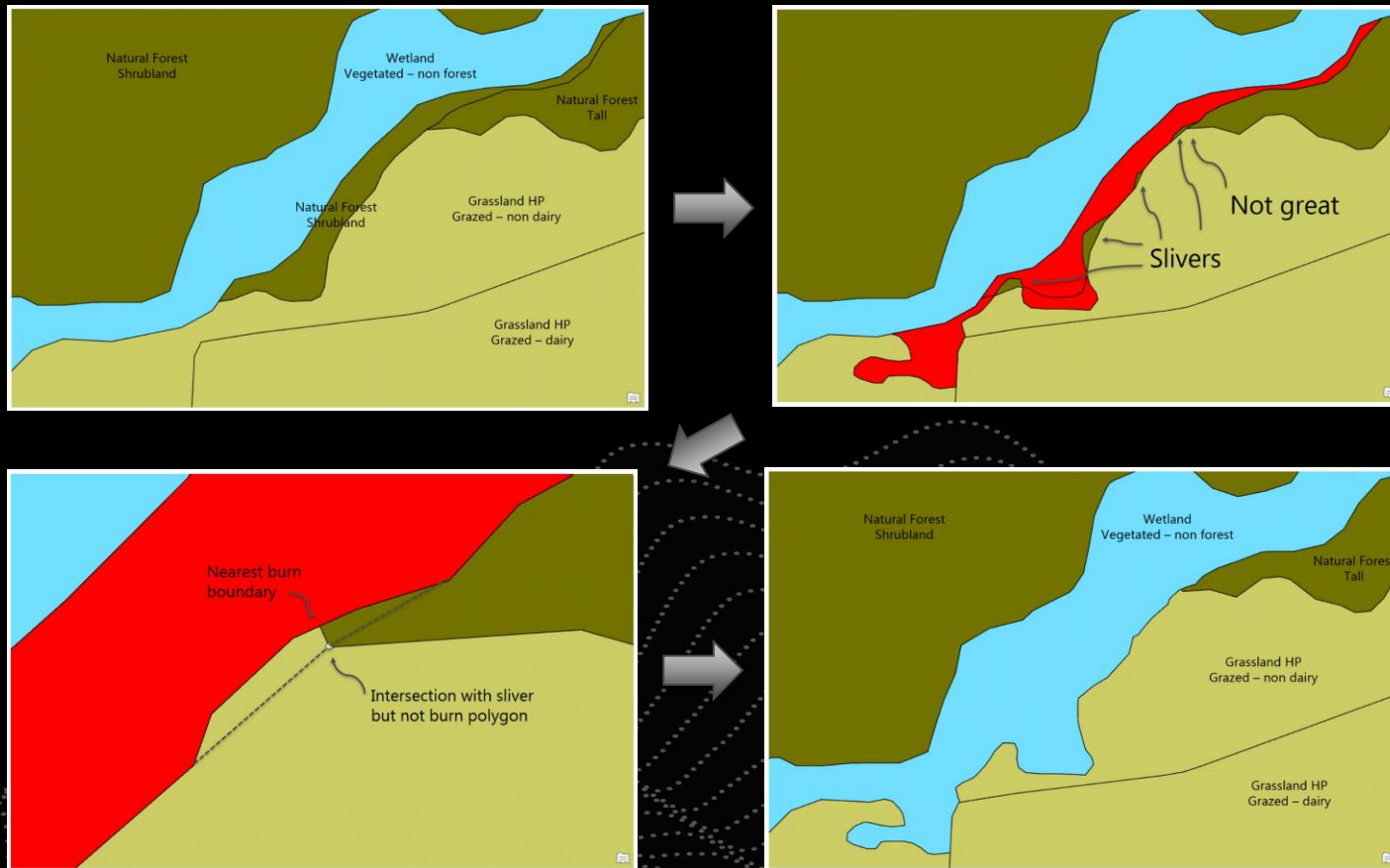
Spilt the sliver and manipulate, connect or remove aspects of the intersections to final shape

4. Scripted automation of geospatial processing

Python scripting was used to automatically digitise 85% of change areas, including:

- snapping of polygon boundaries to existing LUM boundaries
- detection, removal and integration of sliver polygons
- sophisticated replication of decision making for point and line matching by rule logic.

We also automated associated tabular information (including subclasses from ancillary datasets) using advanced geospatial processing to incorporate change area attribute updates.



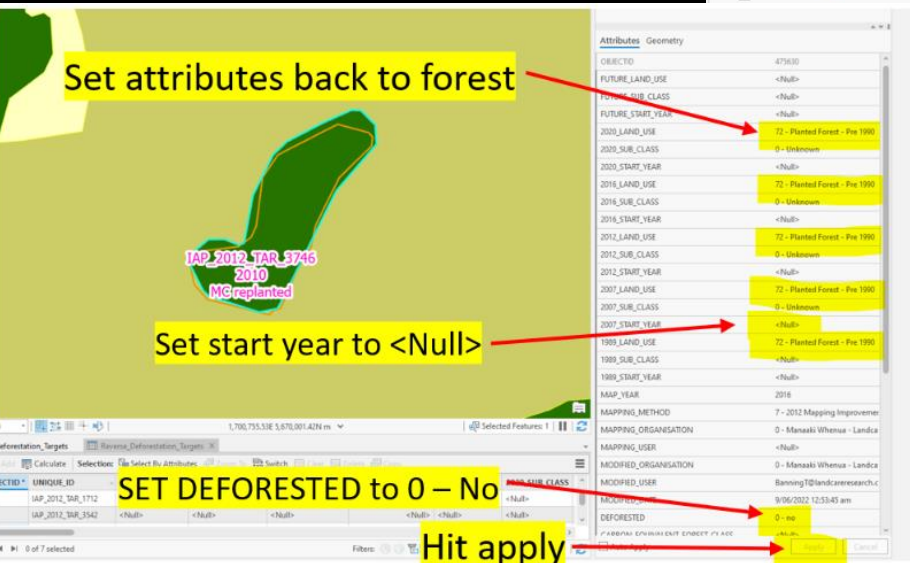
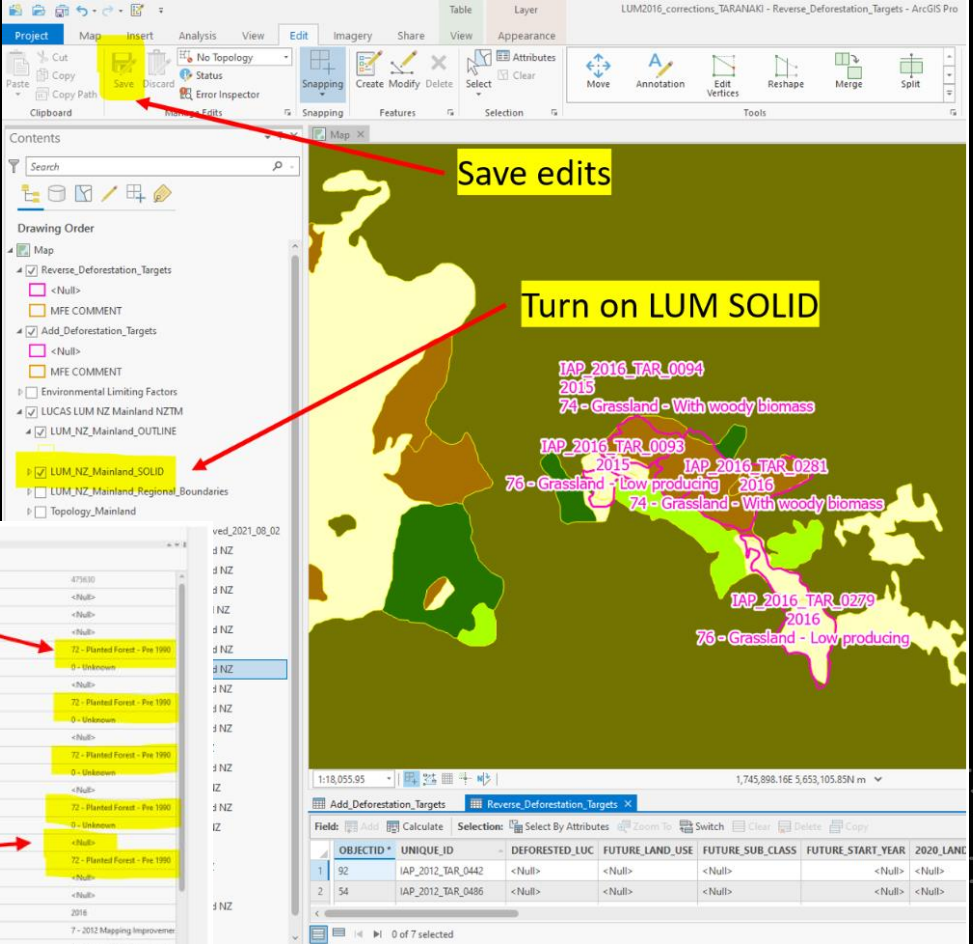
5. Digitising complex and multi-time step land use change

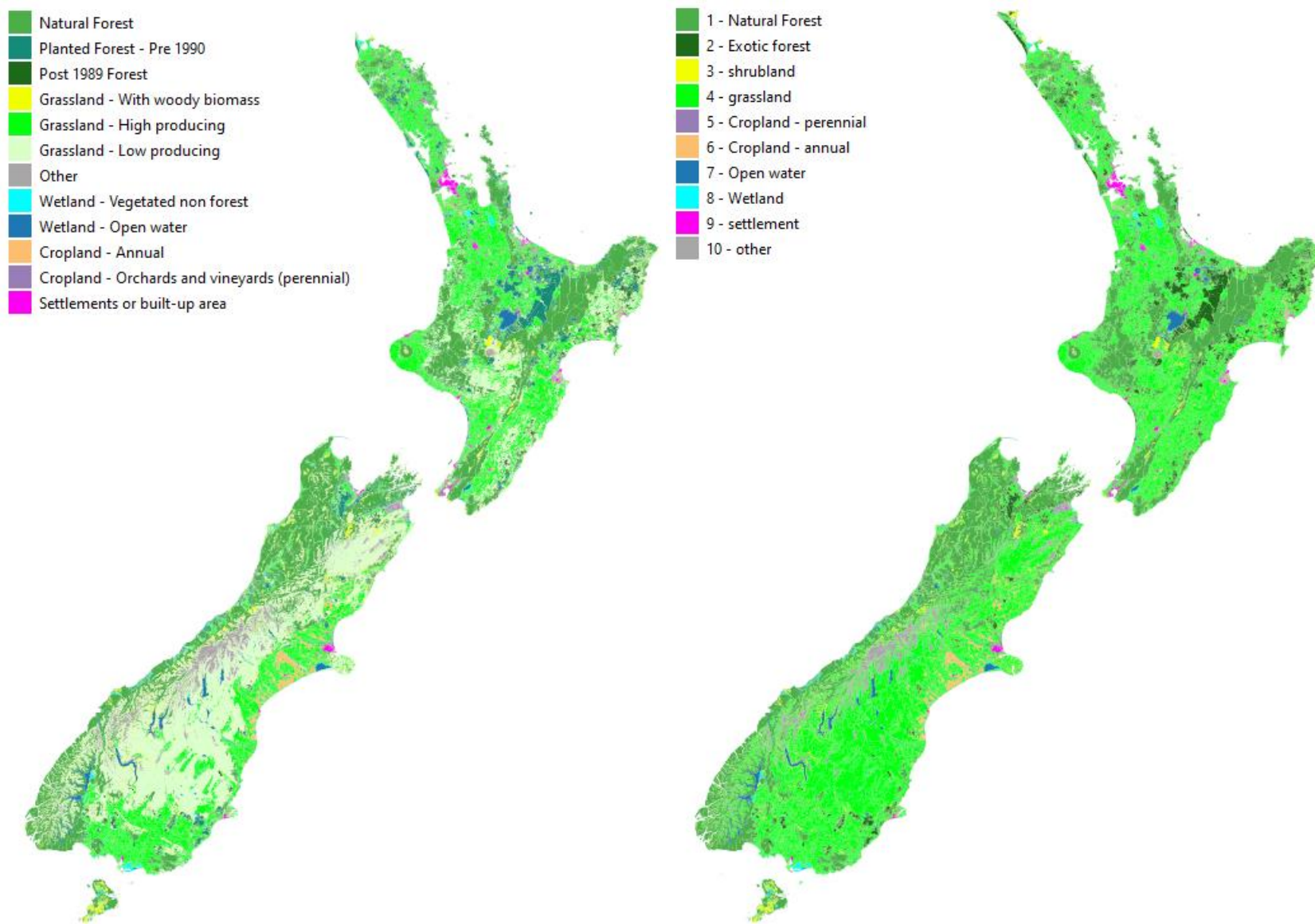
Only 15% of land use change required manual processing due to complexity of boundaries and historical change. Live remote editing was used in an ArcGIS web feature service, with rule-based control, topology validation and process-driven assessments.



Geospatial team editing in ArcSDE feature service

- Version management or using Regional Templates
- Individual ownership over classes to begin with
- Sequence editing with versions shifting to editor
- Digitising of target polygons
- Updating of attribute fields with logic rules
- QA and topology checking
- Completed regions handed over to MFE





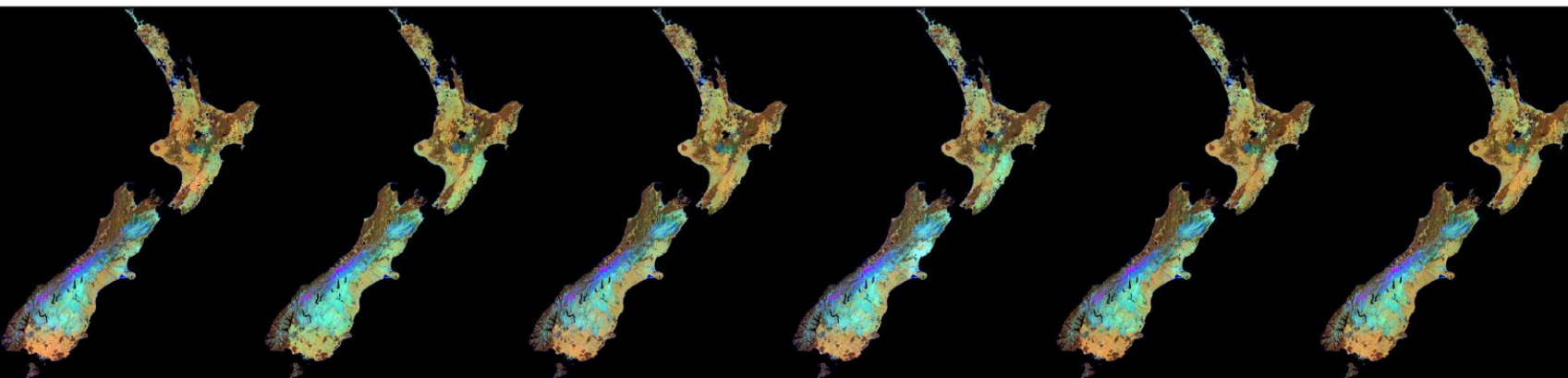
Original land use layer (LUM 2016, left) compared to the new land cover layer (LUM-LC 2016, right).

Investigation into potential automation using Artificial Intelligence: LUM Deep Learning model, training and corrections (2016 and 2020)

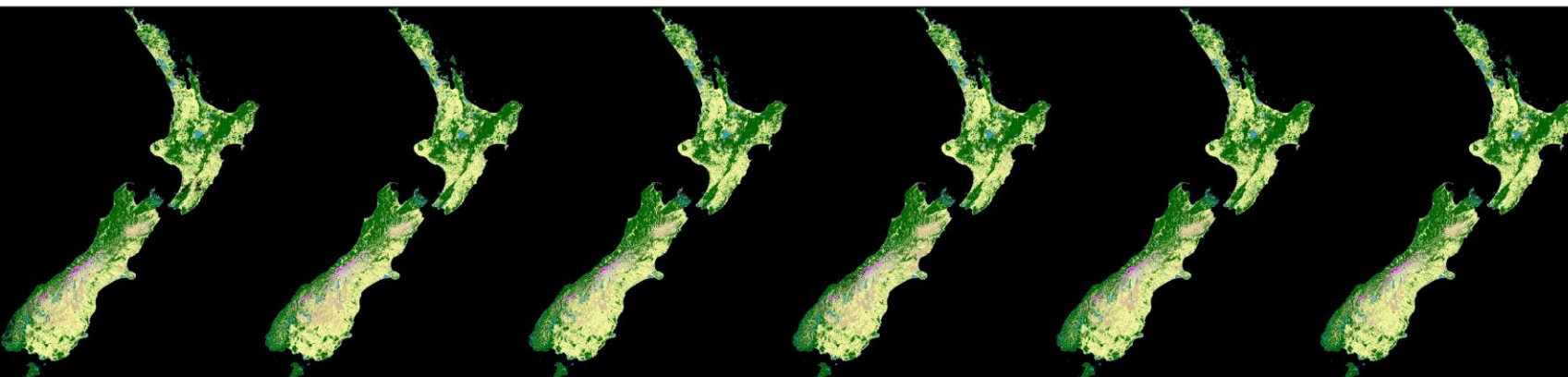
- LUM 2016 DL map – NZ
- LUM 2016 DL corrections
- LUM 2020 DL prediction
- A report of findings

Successfully trained models to automatically generate a land use-based land cover map from satellite Imagery

Partial success detecting forest change (~40%)



2016 2017 2018 2019 2020 2021



Using the same Sentinel-2A national cloudfree mosaics, we can also produce:
Annual Woody Vegetation



Available online at www.sciencedirect.com
SCIENCE @ DIRECT®
Remote Sensing of Environment 90 (2004) 116–125

Remote Sensing of Environment
www.elsevier.com/locate/rse

The spatial distribution of indigenous forest and its composition in the Wellington region, New Zealand, from ETM+ satellite imagery

John R. Dymond^a, James D. Shepherd

Landcare Research, Private Bag 11052, Palmerston North, New Zealand

Received 8 June 2003; received in revised form 12 November 2003; accepted 14 November 2003

Remote Sensing Letters, 2014

Vol. 5, No. 7, 637–641, <http://dx.doi.org/10.1080/2150704X.2014.950761>




Accurate registration of optical satellite imagery with elevation models for topographic correction

James D. Shepherd^a, John R. Dymond^{a*}, Sam Gillingham^b, and Peter Bunting^c

^aLandcare Research, Palmerston North, New Zealand; ^bLandcare Research, Lincoln, New Zealand; ^cDepartment of Geography, University of Aberystwyth, Aberystwyth, UK

(Received 25 May 2014; accepted 19 July 2014)



Remote Sensing of Environment 75 (2001) 350–359
www.elsevier.com/locate/rse

Remote Sensing of Environment

A simple physical model of vegetation reflectance for standardising optical satellite imagery

J.R. Dymond^a, J.D. Shepherd^a, J. Qi^b

^aLandcare Research, Palmerston North, New Zealand
^bMichigan State University, East Lansing, MI USA

Received 20 March 2000; accepted 10 August 2000



INT. J. REMOTE SENSING, 2003, VOL. 24, NO. 17, 3503–3514



Correcting satellite imagery for the variance of reflectance and illumination with topography

J. D. SHEPHERD^a and J. R. DYMOND

Landcare Research, Palmerston North, New Zealand

(Received 23 October 2000; in final form 15 March 2002)

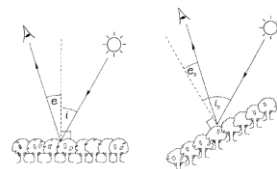
2618
IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 37, NO. 5, SEPTEMBER 1999

Correspondence

Correction of the Topographic Effect in Remote Sensing
John R. Dymond and James D. Shepherd

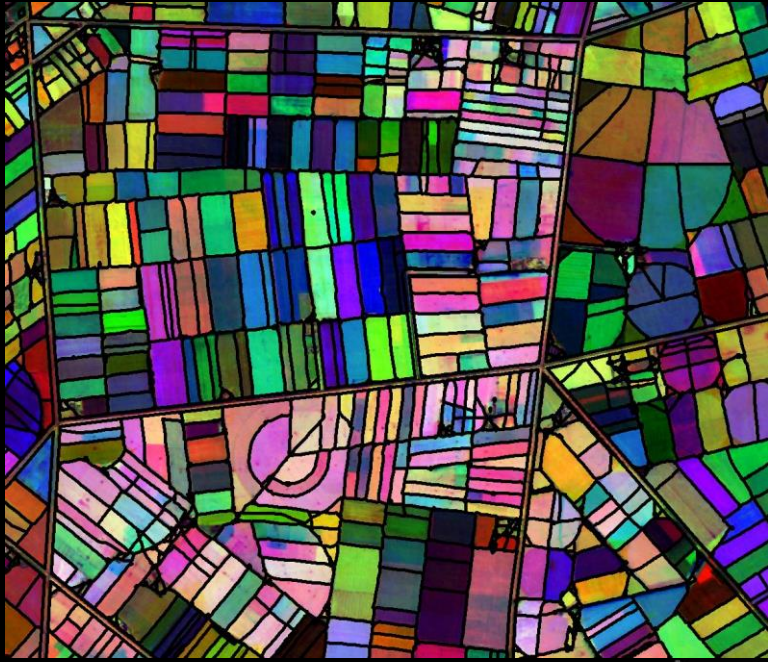
Abstract—We derive a formula for the dependence of vegetation-canopy reflectance on terrain slope (visible light only). Reflectance is inversely proportional to the sum of cosine of incidence angle and cosine of exitance angle. Laboratory measurements of miniature forest canopies set up on inclined slopes compare well with predicted reflectances.

Index Terms—Bidirectional reflectance, slope angle, topographic effect, vegetation reflectance.



I. INTRODUCTION

Paddock Segmentation and boundary mapping



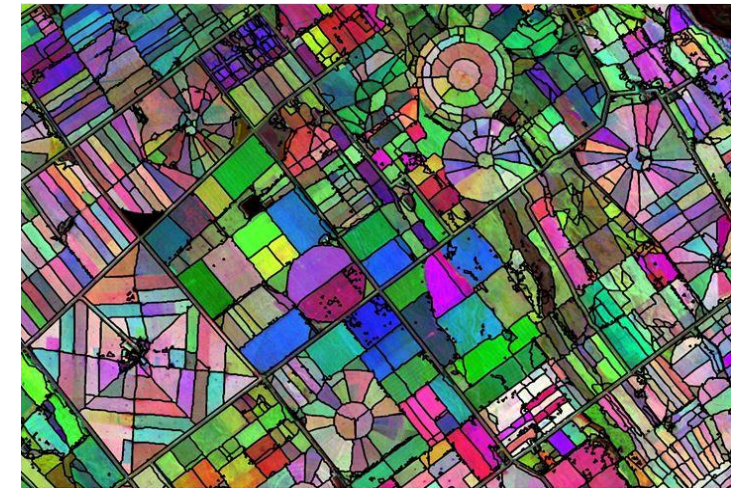
Small gaps bridged, dangles removed,
polygons built



Compare to map drawn from
hi-res image

Using the same Sentinel-2A
national cloudfree mosaics,
we can also produce:

Paddock Boundaries



Boundary Delineation of Agricultural Fields in Multitemporal Satellite Imagery

Heather C. North , Member, IEEE, David Pairman , Member, IEEE, and Stella E. Belliss 

Using the same Sentinel-2A national cloudfree mosaicking techniques, we can also produce:
Seasonal Crop Mapping



Legend

Winter forage crop

- WF kale
- WF brassica - general
- WF fodder beet
- WF cereal (e.g. oats)
- Winter grazing - other (sufficiently intensive to cause bare ground in winter)

Not winter forage crop

- Bare soil/stubble/dead vegetation
- Autumn-planted arable crop or pasture (or pasture re-growing after summer dry)
- Pasture (throughout the April to early October period of the imagery)
- Lucerne
- Low-cover vegetation or undeveloped grassland

Unknown whether winter forage

- Unknown vegetation
- Unknown
- Masked out (not agricultural land)



1 0 1 2 3 4 5 Kilometres



Legend for crop group classes

- Pasture (or lucerne)
- Grain (wheat, oats, or barley)
- Grass seed or barley
- Maize (silage)
- White clover seed
- Peas or brassica/radish seed
- Potatoes (or carrot seed)
- Brassica (winter livestock forage)
- Pasture (lower probability)
- Unknown crop (lower probability)
- Bare soil
- Unknown



Legend for land use/timing classes

- Pasture - irrigated
- Pasture - dryland (and newly-planted pasture)
- Crop planted early autumn (e.g. grain; or brassica/grass/clover seed)
- Crop planted late autumn (e.g. grain crop or grass seed)
- Crop planted winter (e.g. grain crop)
- Crop planted spring (e.g. grain, peas, brassica seed)
- Crop planted summer, short peak (e.g. potatoes)
- Crop planted summer, long peak (e.g. maize for silage)
- Winter livestock forage - just planted Nov-Dec
- Bare soil (Nov-Jan)
- Unknown

5 0 Kilometres

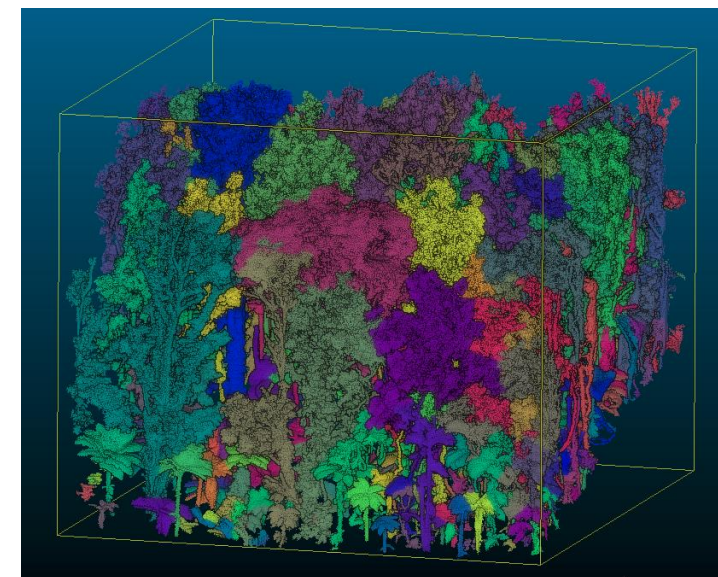
b.

a.

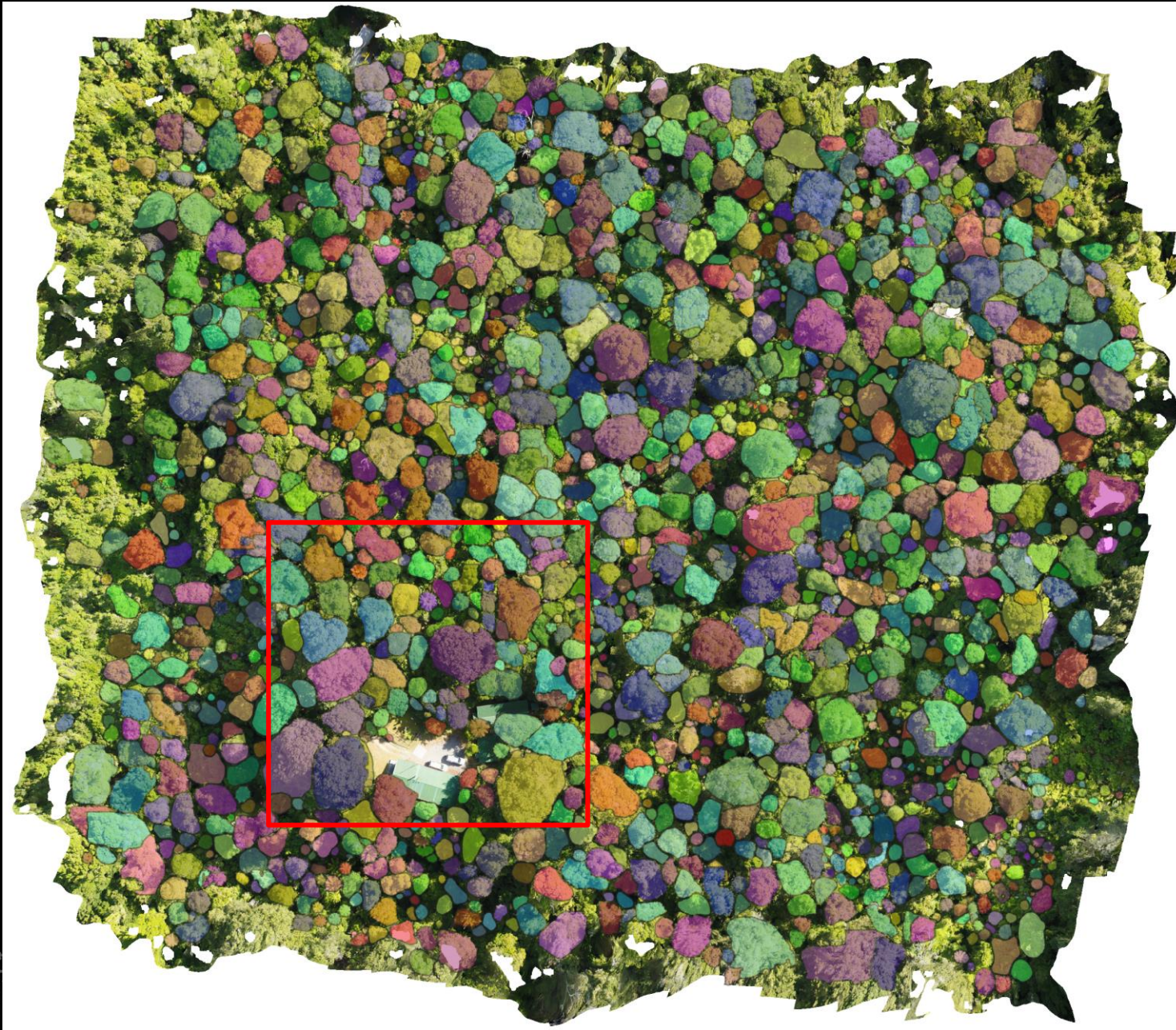
LiDAR use for individual tree segmentation



1 jan@debian: ~/Videos/Screencasts

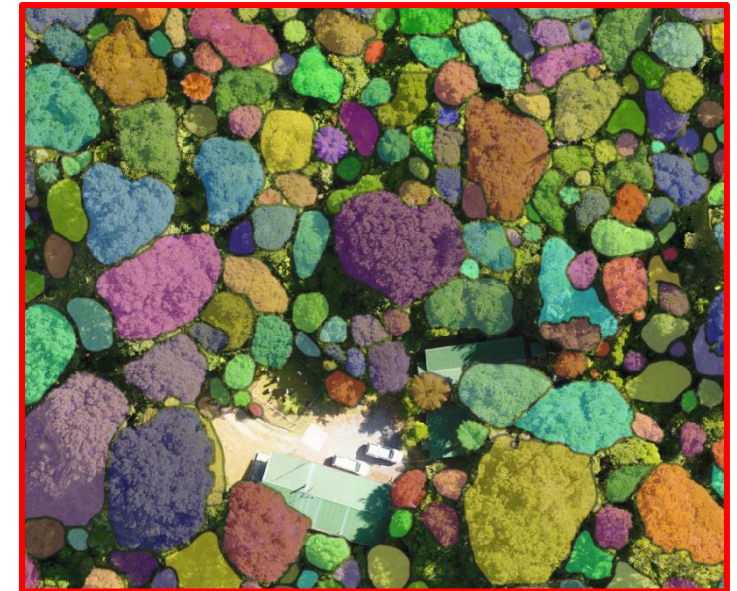


Tree Crown Segmentation from RGB drone imagery

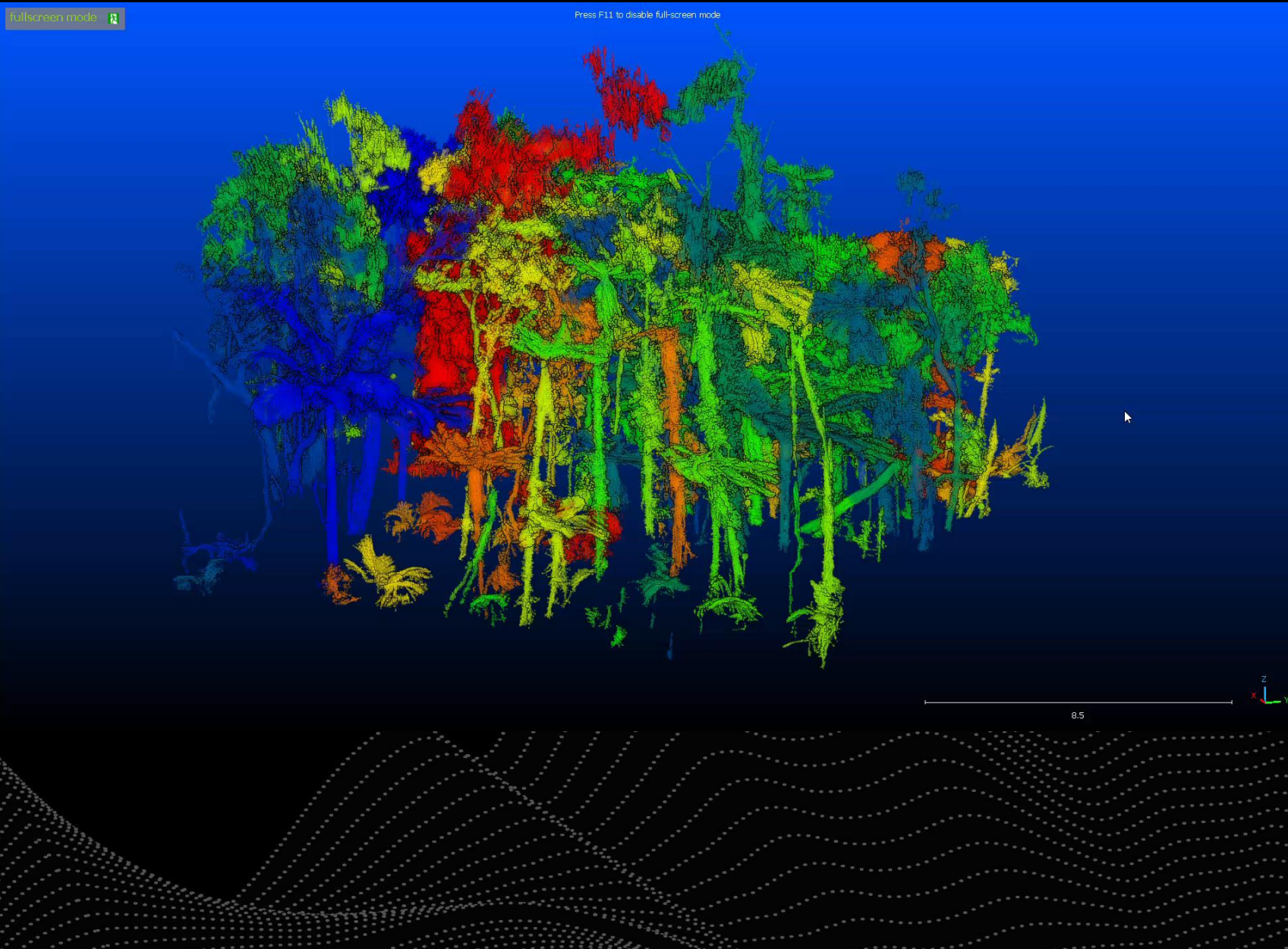
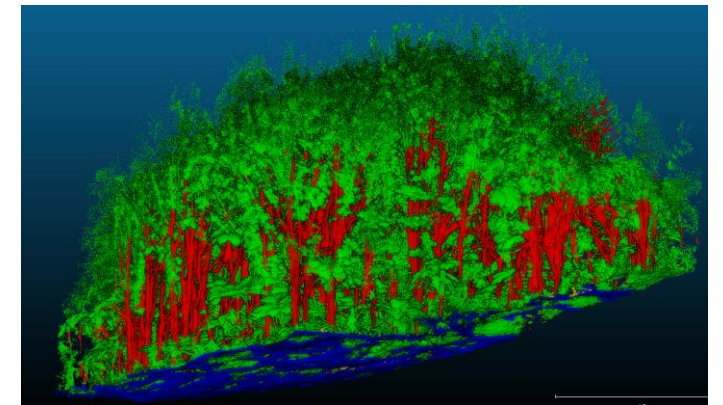


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Tree Crown segmentation
and canopy models using AI

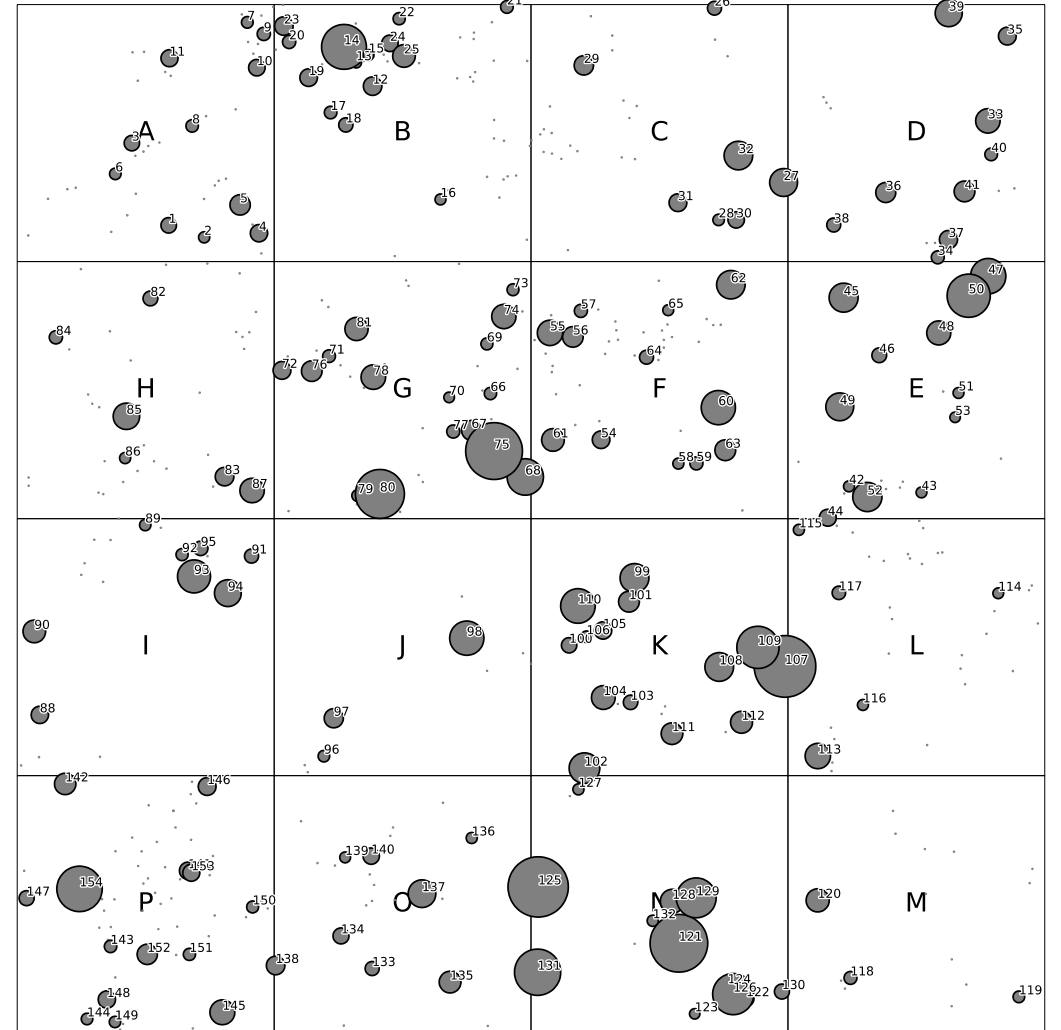
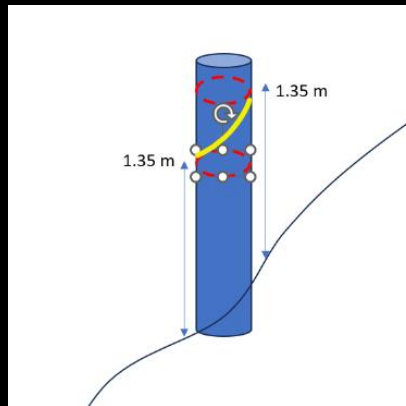
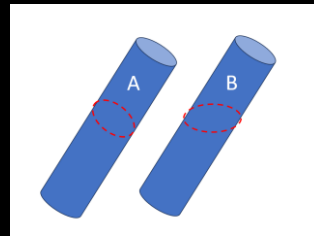
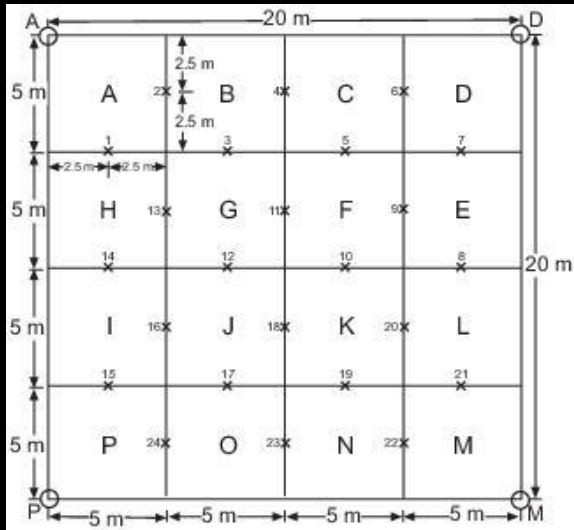
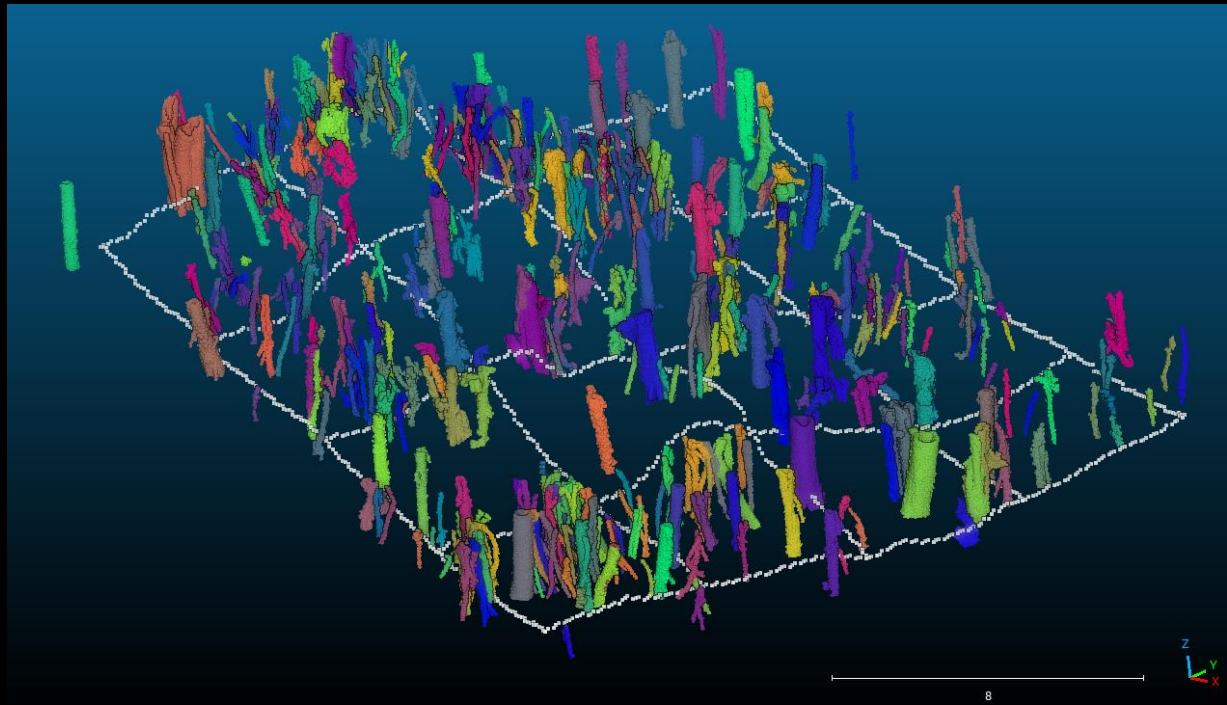


Using the latest advancements in LiDAR, we are investigating methods to measure carbon stocks, woody biomass and other carbon measurement techniques.





Carbon forest plots can be informed by LiDAR stem and branch cylinder models.



Tree locations transformed onto a square sub plot grid of 5x5 metre. The circles indicate the approximate stem radius.



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Urban Tree Map Explorer *Experimental*

MAP ABOUT PRIVACY

Map Layers

- Tree Crowns
- Tree Crowns
- Aerial Photography

1000 m

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