

Tools and techniques for environmental decision-making: Remote sensing of landscape level biodiversity

SD Jones, A Lechner, N Miura, KJ Reinke, K Sheffield, E Farmer.
Geospatial Science, Royal Melbourne Institute of Technology.

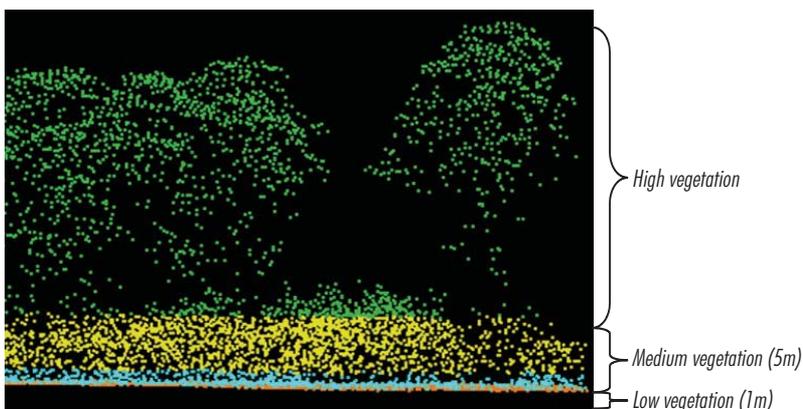
Biodiversity assessments currently undertaken in Australia (habitat hectares, biometric, NVC –Tasmania, to name but a few) use plot based assessments to measure key attributes or metrics. Our team at Landscape Logic have been working to determine the utility of remote sensing in producing landscape-level assessments of these variables. This presentation gives an overview of this work and highlights two studies underway to improve our quantification of landscape-level biodiversity. The first project explores landscape configuration and issues of data uncertainty. Remote sensing is widely used in ecology to measure and monitor patch size, shape and connectivity. However, choice of: satellite sensor, spatial and spectral resolution, classification technique and class description, can produce large differences in predictions of extent and patchiness and the accuracy of these predictions varies considerably. This section of the presentation will focus on providing case studies, guidance and tools for producing maps of ecological parameters.

The second project explores the utility of LiDAR (airborne laser scanning) for predicting structural components of landscape level biodiversity. Waveform LiDAR systems generate discrete pulses of energy (at 1–1.5um) which bounce off landscape objects. Each of these returns is time stamped and has range and distance information allowing the structure to be mapped as 3D images. Results show the system's utility in assessing canopy cover, course woody debris and stem density.

Relevant publications

- Lechner AM, Jones SD and Bekessy SA. (2008) A study on the impact of scale dependent factors on the classification of land-cover maps. In *Quality Aspects in Spatial Data Mining*. (Ed. A Stein, J Shi and B Wietske). Chapman and Hall/CRC Press.
- Reinke KJ and Jones SD (2006). Implementation of a Prototype Toolbox for Communicating Spatial data Quality and Uncertainty Using a Wildfire Risk Example. In *Spatial Data Handling*. (Eds. by A Riedl, W Kainz, G Elmes). Springer, pp. 321-337.
- Hunter GJ, Jones SD, Bregt A and Masters EG (2003) Spatial Data Quality. In *Advanced Geographic Information Systems*. (Eds. CMB Medeiros). Encyclopedia of Life Support Systems (EOLSS), developed under the auspices of the UNESCO, EOLSS Publishers, Oxford, UK (www.eolss.com) *Advanced Geographic Information Systems Volume I*, ISBN 978-1-905839-91-9; *Advanced Geographic Information Systems Volume II* ISBN 978-1-905839-92-6.
- Reinke R, Jones SD (2006) Issues Arising from the Integration of Regional Scale Remotely Sensed Data with Site Based Assessments of Native Vegetation Condition, *Ecological Management & Restoration Vol 7, Supp 1*, pp. 18-23, ISSN 1442-7001.
- Miura N, Jones SD (2008) Characterising the ecological structure of a dry Eucalypt forest landscape. *SilviLaser 2008*, Sept. 17-19, 2008, Edinburgh, UK.

Eucalyptus amygdalina and *Leptospermum scaparium* (common teatree) in the Rubicon catchment (1 of 14 sites surveyed).



Prof Simon Jones

Simon.Jones@rmit.edu.au

Royal Melbourne Institute of Technology

Day 2, 2.20pm

Area of work: Remote sensing of environment

Specialty: Linking biological phenomena with earth observation and associated issues of scale.

Take-home messages:

1. The selection of remote sensing used to map vegetation (satellite and aerial sensor, spatial and spectral resolution, vegetation class description) can significantly influence estimates of extent and patchiness.
2. By understanding the sources of this variation, we have demonstrated that we can improve the consistency and accuracy of remote sensing based assessments of biodiversity parameters.
3. LiDAR (airborne laser scanning) can be used to generate 3D images of vegetation, revealing structural characteristics from canopy top to ground level in great detail.
4. Our research is demonstrating the utility of LiDAR in measuring canopy cover and course woody debris with considerable accuracy relative to site based measurement.

Tools and techniques for environmental decision-making:
Remote sensing of landscape level biodiversity



**SD Jones, A Lechner, N Miura,
KJ Reinke, KJ Sheffield, E Farmer**

(School of Mathematical and Geospatial Science,
Royal Melbourne Institute of Technology)

Stakeholder context:

Who's doing what?

RS of Australian Native Vegetation

| Task | CMO's | Fed/State Govt | Science Community | Int'l Protocols | NGO's |
|-------------------|--------------|---------------------------|------------------------------|----------------------------|--------------|
| Mapping | some | yes | some | rare | rare |
| Monitoring | yes | yes | some | yes | yes |
| Validation | some | some | yes | increasingly | no |

Components measured within a forest NVC assessment

tree canopy
cover / health

large old
trees and
canopy
health

patch size &
connectivity
(neighbourhood & core
area)

understorey life
forms diversity
and cover

recruitment of
woody species

Logs / CWD
organic litter

lack of weeds

Overview

Tools and techniques:

- **RS for landcover mapping (cover type extent and configuration)**
 - Simplest task
 - Widely attempted (AGO NCAS, state government mapping agencies)
- **Emerging RS technologies for characterising biodiversity at a landscape scale**



RS landcover

(mapping cover type extent and configuration)

What are the Scale and Accuracy effects on the characterization of Landscape Pattern?

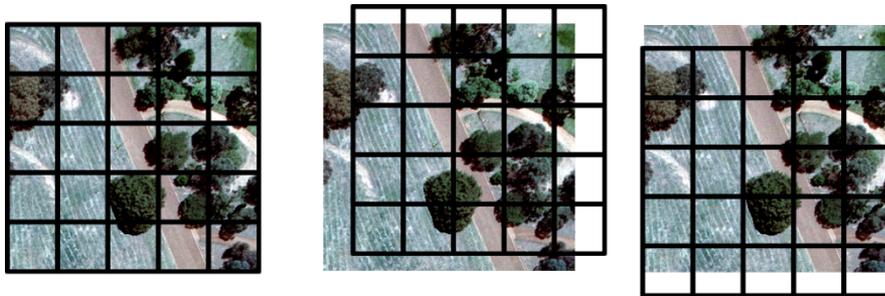
Synoptic Sensing Systems are characterised by:

- multi-spectral (7+ bands) capability centered on visible, near infrared - mid-infrared - thermal regions of the electromagnetic spectrum;
- a long length of archive (20-30+ years);
- a compromise or trade-off between resolutions,
 - i.e. moderate spatial, radiometric and spectral resolutions and a good temporal resolution;
- Low purchase cost and wide 'swath' coverage

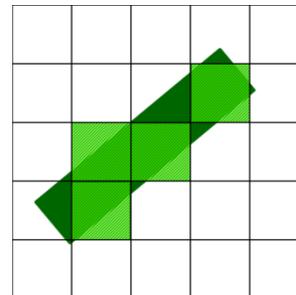
High Spatial Resolution Satellite Sensors are characterised by:

- 3 - 4 spectral bands centred on the visible / near infrared spectral region;
- Pushbroom sensing technology
- Commercially owned spacecraft and ground receiving infrastructure;
- Targeted data archiving;
- A higher per km² cost (>\$10 per km²).

Remote Sensing of linear features: an assessment of the effects of patch size, length and grid position on the probability of feature extraction.



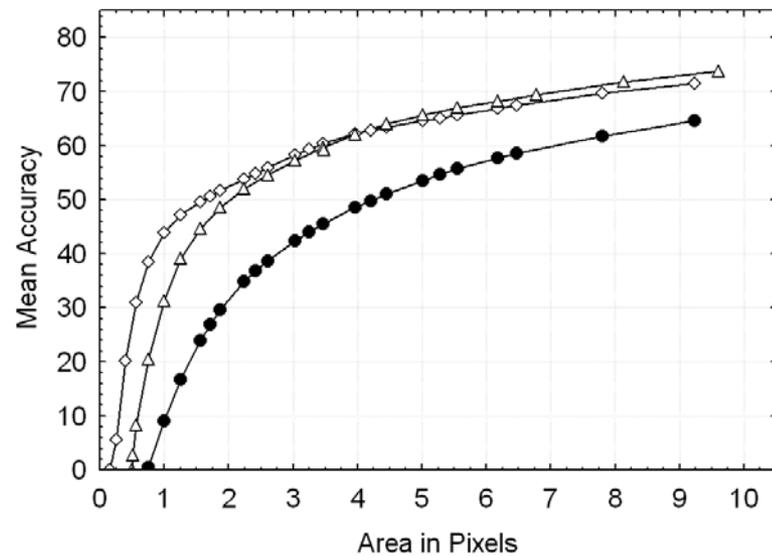
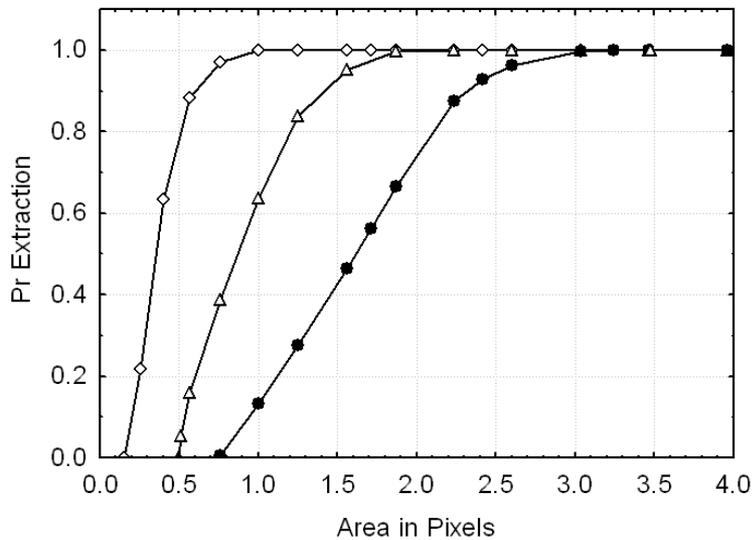
The position of a satellite sensor array's grid is random with respect to features in the landscape. An example of 3 different possible positions of the grid out of an infinite number of possibilities.



A discrete linear strip has been broken up into smaller patches as a result of the relationship between the feature's position and dimensions and the grid position.

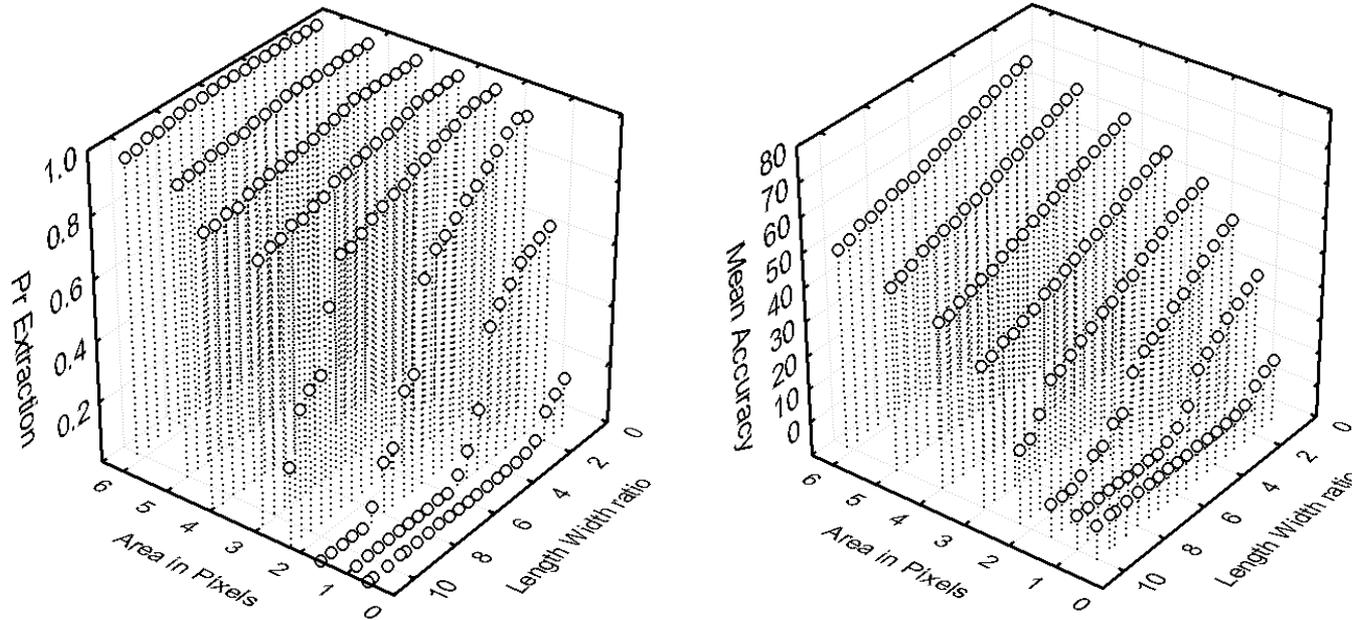


Remote Sensing of linear features: an assessment of the effects of patch size, length and grid position on the probability of feature extraction.



(a) Probability of extracting a square patch and (b) Mean mapping accuracy (Patch Mapping Accuracy = $\frac{\text{Pixels of patch}_{\text{correct}}}{\text{Pixels of patch}_{\text{correct}} + \text{Pixels of patch}_{\text{omission}} + \text{Pixels of patch}_{\text{commission}}}$) of various sized square patches for 3 classification thresholds (.25, .5, .75). Each point corresponds to a sample.

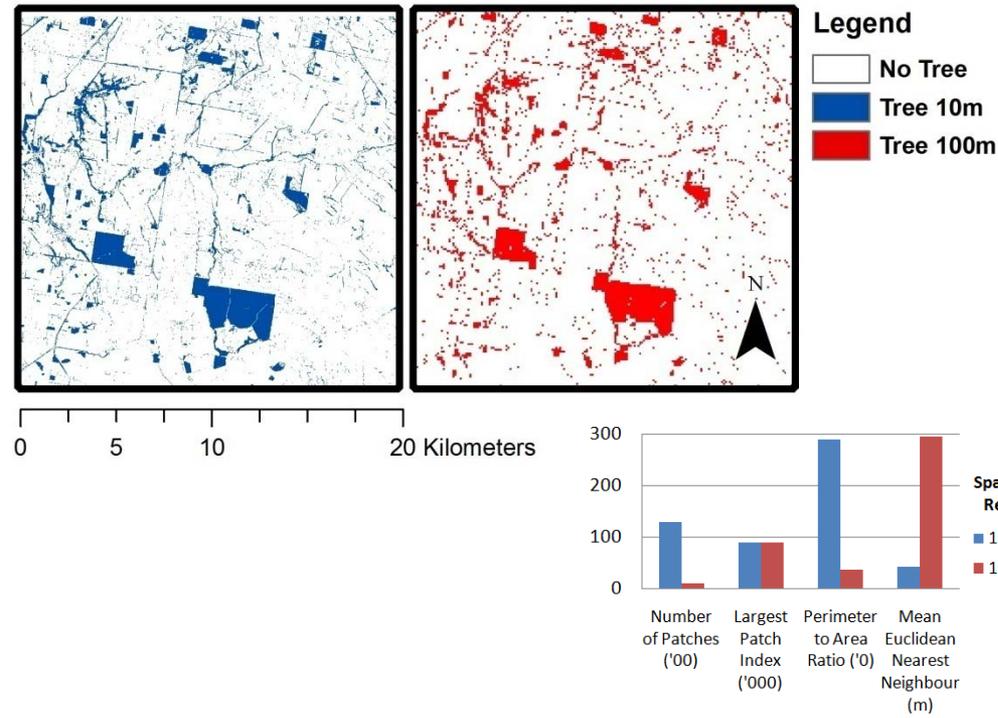
Remote Sensing of linear features: an assessment of the effects of patch size, length and grid position on the probability of feature extraction.



a) Probability of detection and b) Mean Accuracy versus length width ratio and area for a classification threshold of .5 (patch and matrix with equal weighting).



Remote Sensing of linear features: an assessment of the effects of patch size, length and grid position on the probability of feature extraction.



Examine effect on Landscape Scale at low resolution

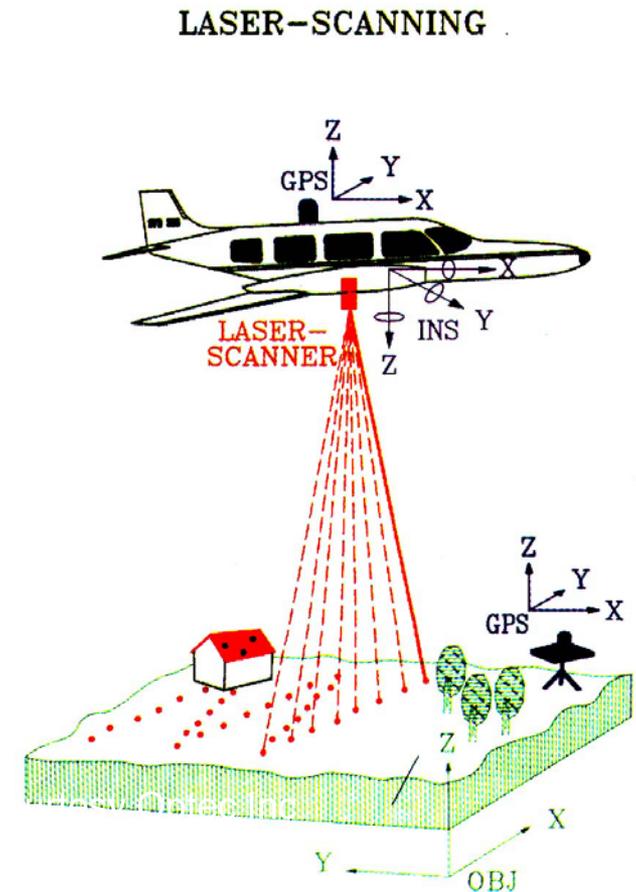
- Linear strips disappear
- Large areas are unaffected
- Not recorded by confusion matrix
 - Global statement of accuracy
- Landscape pattern is changed

Emerging RS technologies

(characterising biodiversity at a landscape scale)

LIDAR (Light Detection And Ranging)

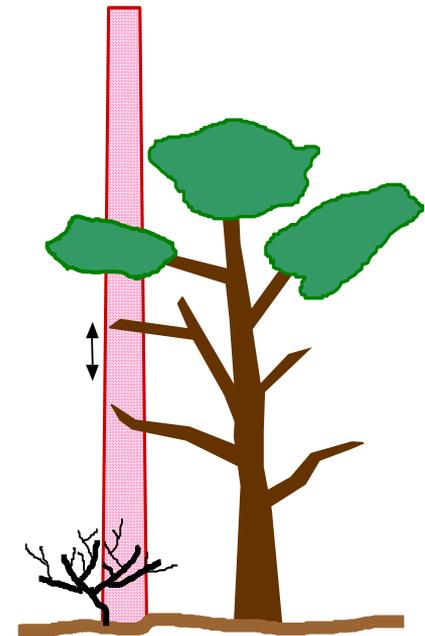
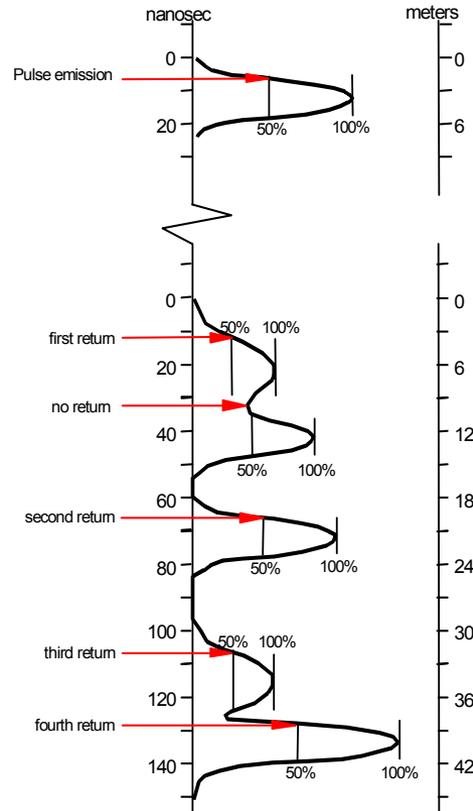
- Active airborne sensor emits several thousand infrared laser pulses per second (10,000 – 300,000)
- Operates on principle that if location and orientation of laser scanner is known, we can calculate a range measurement for each recorded echo / return from a laser pulse
- Components of system include INS (inertial navigation system), airborne differential GPS, and laser scanner
- Range measurements are post-processed and delivered as XYZ coordinates



Courtesy: Optech inc.

LIDAR for Vegetation Condition Surveys

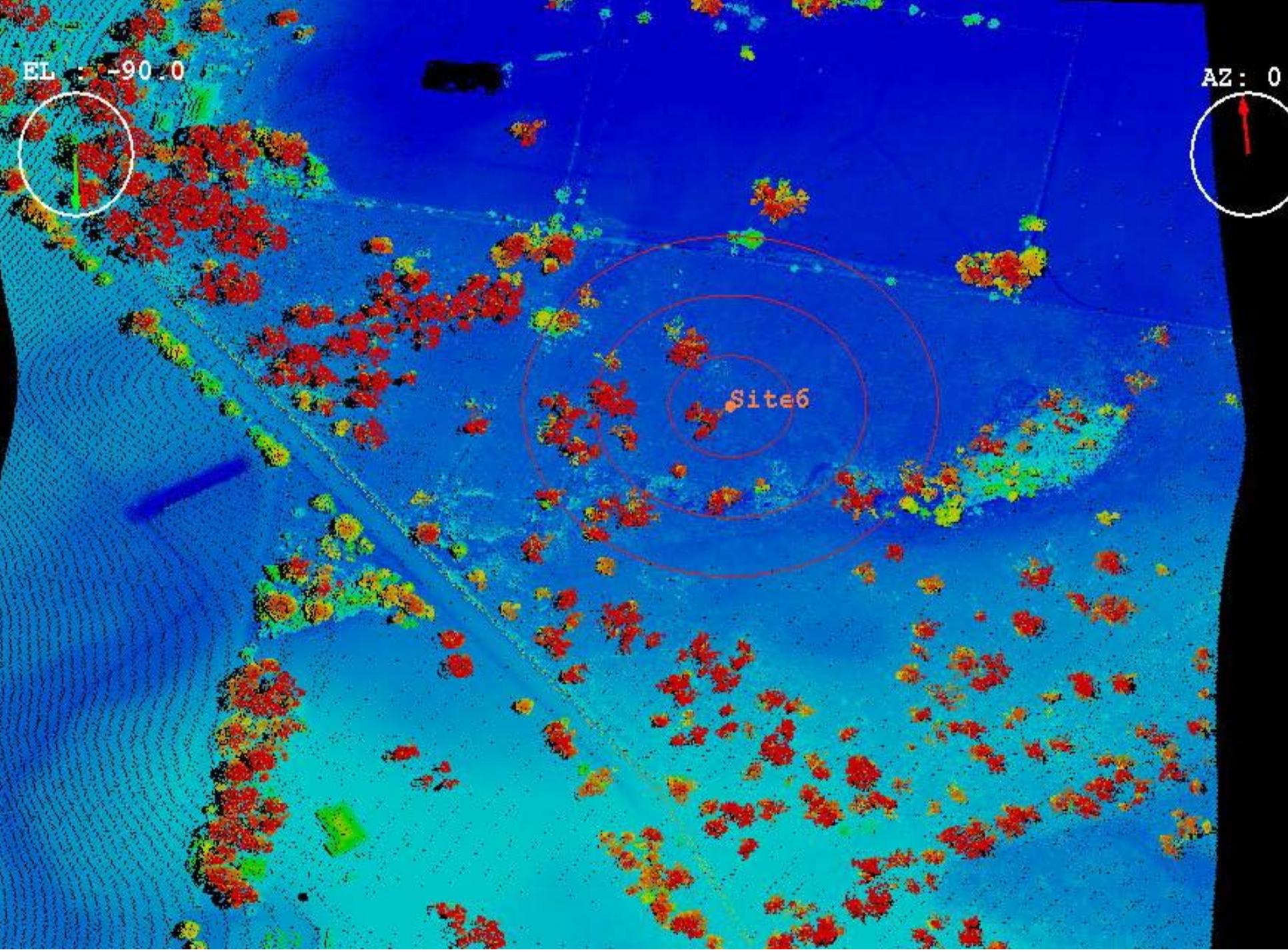
- **“Continuous waveform” vs. “discrete return” systems**
 - LIDAR systems can acquire multiple measurements from a single laser pulse
- LIDAR data represent direct measurements of three-dimensional vegetation structure



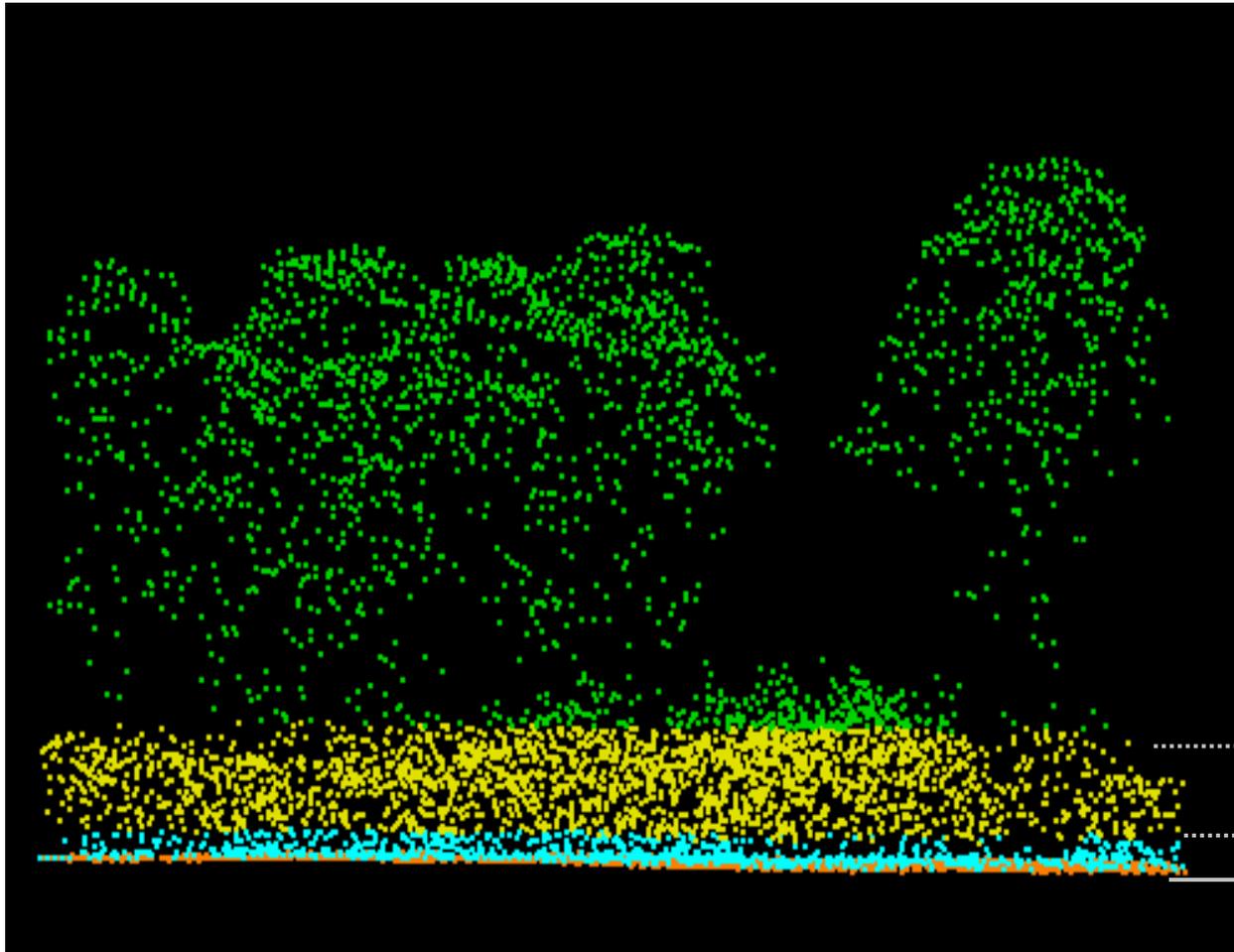
EL : -90.0

AZ : 0

Site6



Waveform Methods



High vegetation

5m

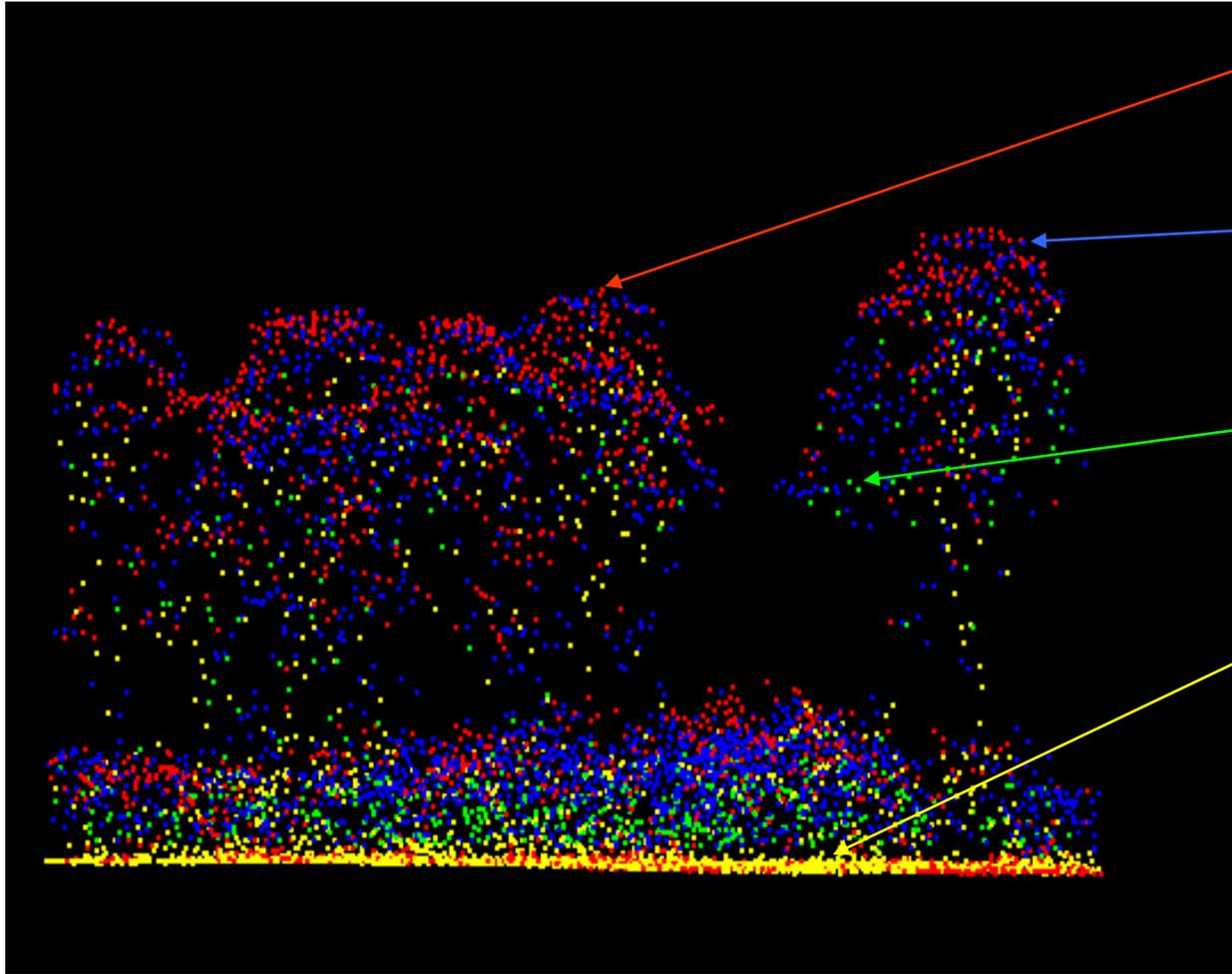
Medium vegetation

1m

Low vegetation

Ground

Waveform Methods



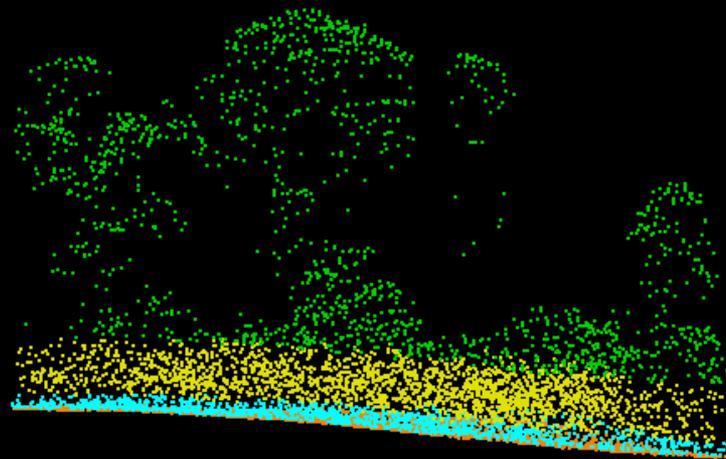
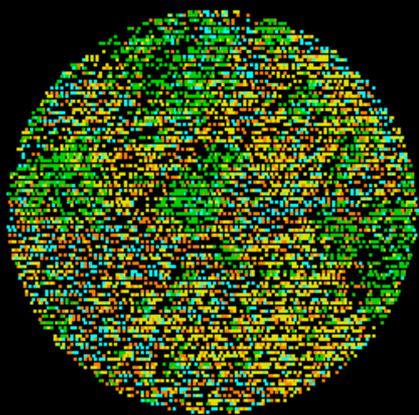
Type1
Singular

Type2
1st of many returns

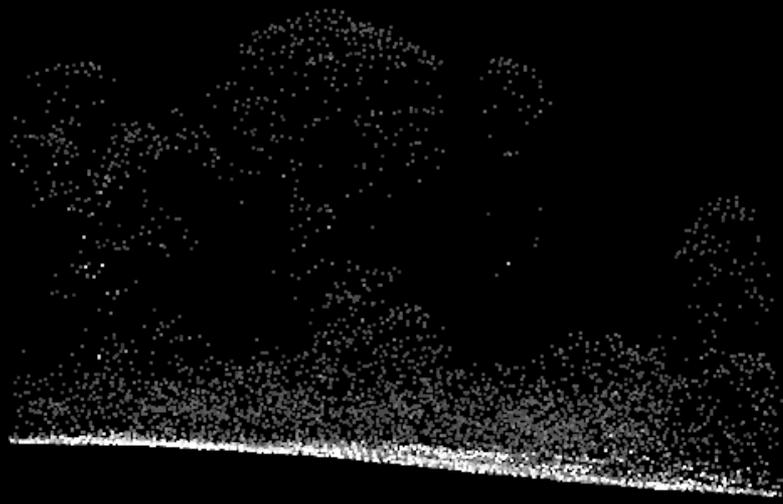
Type3
Intermediate

Type4
Last of many returns

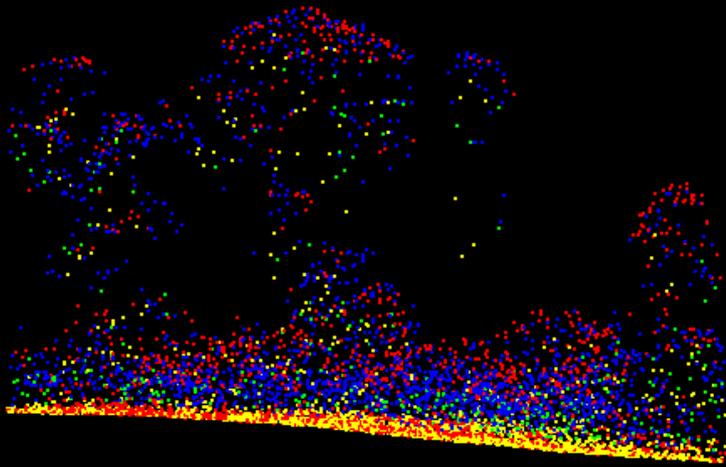
site 8a



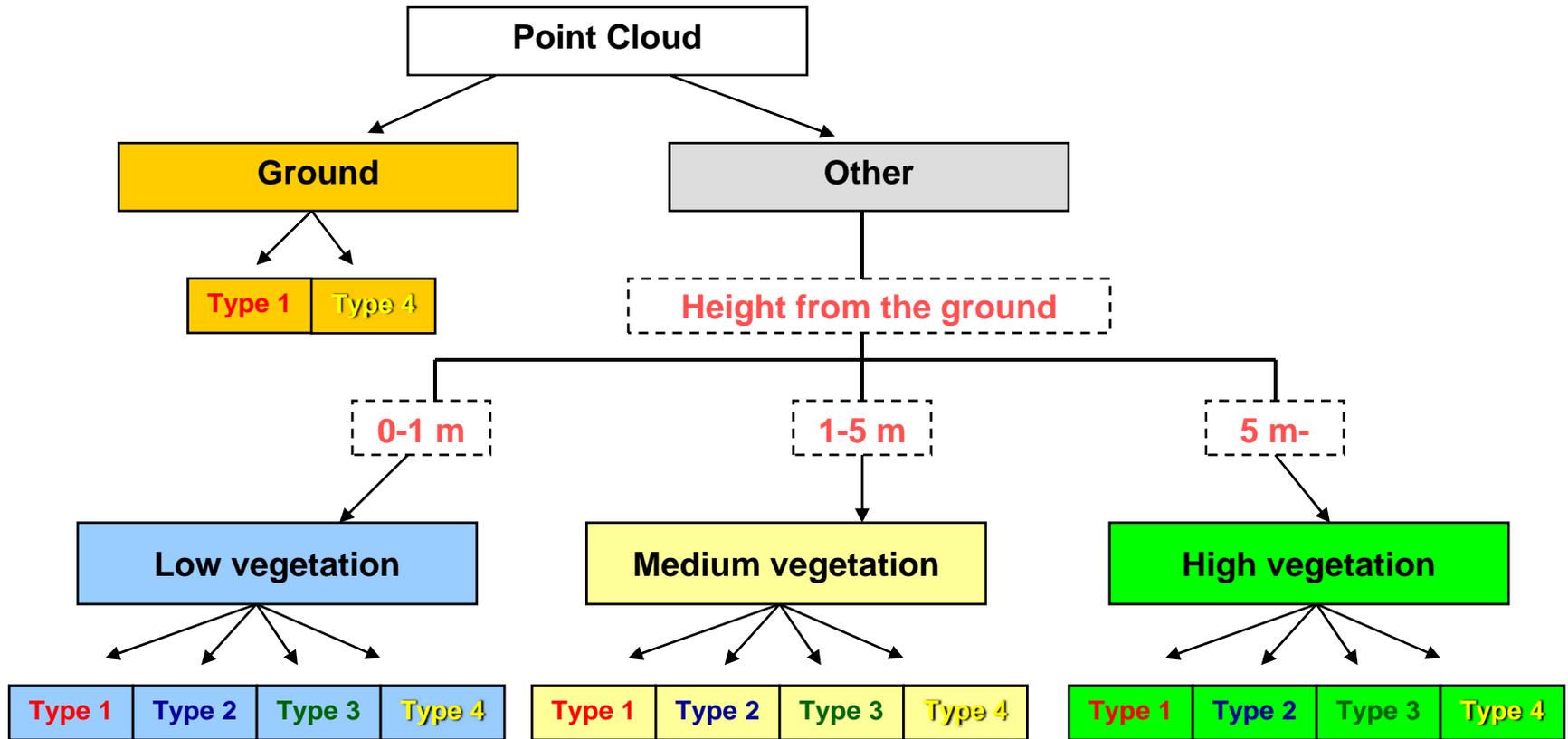
View 3



View 4



Waveform Methods



Correlation

Type1; Singular **Type2; 1st of many returns** **Type3; Intermediate** **Type4; Last of many returns**

Field data

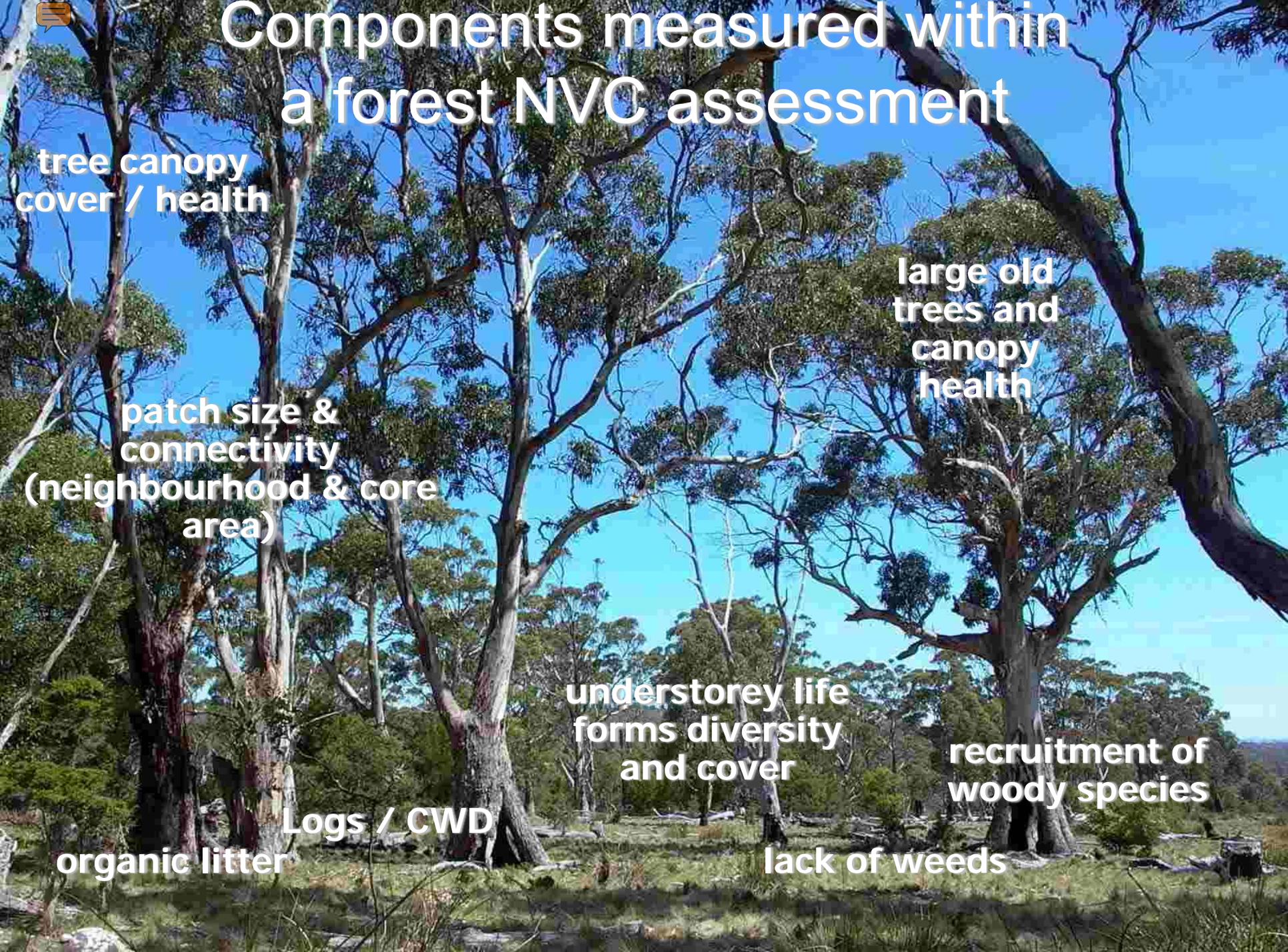
Strength of correlation between LiDAR derived vegetation condition attributes and ground based surveys

Correlations

| | | LAI | TotalVolCWD | MeanCanopy_1 | MeanCanopy_2 | MeanLowVeg | MeanHeight |
|-----------------------|---------------------|-----------|-------------|--------------|--------------|------------|------------|
| lowveg presence | Pearson Correlation | .907(**) | 0.096 | -.901(**) | -.898(**) | .764(**) | -0.056 |
| | Sig. (2-tailed) | 0.000 | 0.745 | 0.000 | 0.000 | 0.001 | 0.850 |
| CC_return2 | Pearson Correlation | -.838(**) | -0.386 | .879(**) | .881(**) | -.819(**) | -0.246 |
| | Sig. (2-tailed) | 0.000 | 0.173 | 0.000 | 0.000 | 0.000 | 0.396 |
| midveg presence | Pearson Correlation | -0.234 | -.612(*) | 0.313 | 0.293 | -0.414 | -.730(**) |
| | Sig. (2-tailed) | 0.442 | 0.020 | 0.275 | 0.309 | 0.141 | 0.003 |
| density of high trees | Pearson Correlation | -0.412 | .609(*) | 0.455 | 0.396 | -0.311 | .803(**) |
| | Sig. (2-tailed) | 0.162 | 0.021 | 0.102 | 0.161 | 0.279 | 0.001 |
| highveg presence | Pearson Correlation | -.583(*) | 0.278 | .653(*) | .667(**) | -0.427 | .616(*) |
| | Sig. (2-tailed) | 0.036 | 0.337 | 0.011 | 0.009 | 0.128 | 0.019 |

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).



Components measured within a forest NVC assessment

tree canopy
cover / health

large old
trees and
canopy
health

patch size &
connectivity
(neighbourhood & core
area)

understorey life
forms diversity
and cover

recruitment of
woody species

Logs / CWD
organic litter

lack of weeds

Thanks to...

- Alex Lechner,
- Naoko Miura,
- Karin Reinke,
- Kathryn Sheffield,
- Elizabeth Farmer
- & Landscape Logic team

