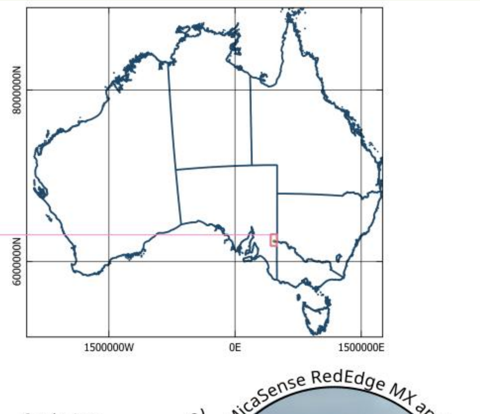
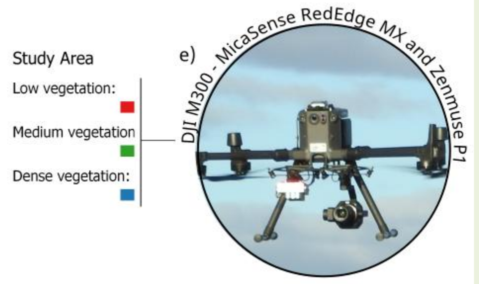
Sensor-agnostic 3D structure mapping pipeline:

from UAS-derived 2D orthophotos and LiDAR point clouds to volumetric training data for 3D U-Net modelling

Laura N. Sotomayor[1]*, Arko Lucieer[1], Megan Lewis[2], Shaun Levick[4], Teja Kattenborn[3]

[1]School of Geography, Planning, and Spatial Sciences, University of Tasmania, Hobart, Australia (laura.sotomayor@utas.edu.au)
[2]School of Biological Sciences, University of Adelaide, Adelaide, Australia [3]Sensor-based Geoinformatics (geosense), University of Freiburg, Germany
[4]CSIRO Environment, Locked Bag 2, Glen Osmond, 5064, SA, Australia

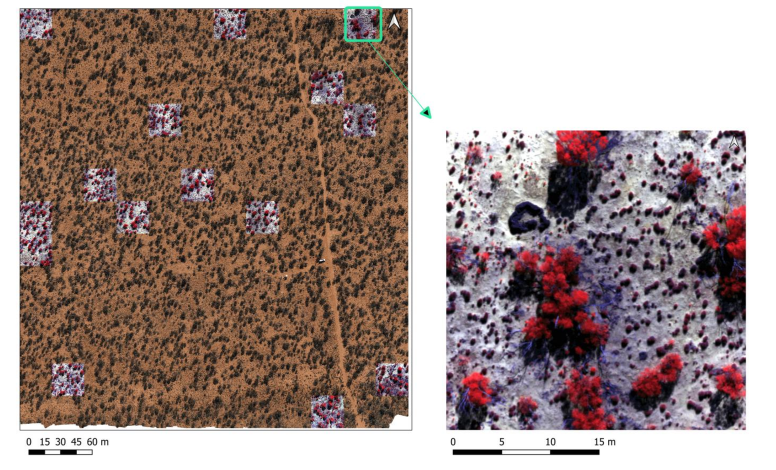




Context:
We present a re-usable sensor-agnostic data pipeline integrating diverse passive (e.g., multispectral orthomosaics) and active (e.g., LiDAR point clouds) remote sensing datasets collected from uncrewed aerial systems (UAS).

Objectives:
To generate volumetric vegetation structure labels by combining 2D UAS-derived inputs with LiDAR data, enabling cost-effective training of 3D U-Net models for semantic segmentation of vegetation strata (herbaceous, shrubs, and canopy).

1_Input data: RBG or MULTISPECTRAL

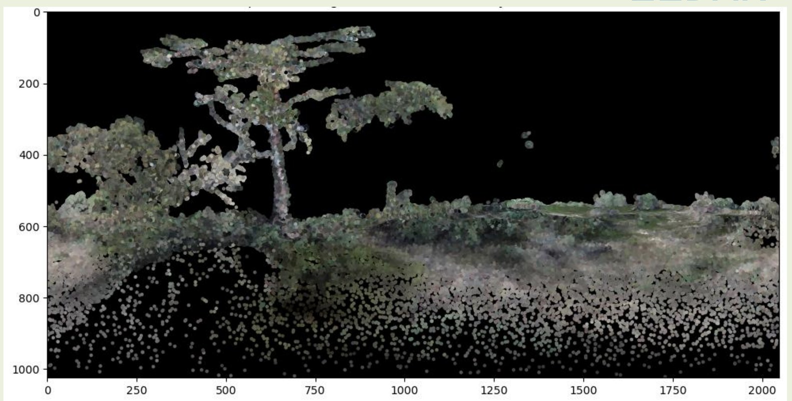


SENSOR:
- DJI Zenmuse P1
- MicaSense RedEdge-MX

FLIGHT:
- 80 m / 50 m

EXTRACT:
- Channels (R,G,B, Red-edge, NIR)

LiDAR



SENSOR:
- DJI Zenmuse L1 and L2 (1753 pts/m2)
- Riegl VUX-120 (4046 pts/m2)

FLIGHT:
- 50 m above ground level (AGL) vs 80 m

EXTRACT:
- Z (height)

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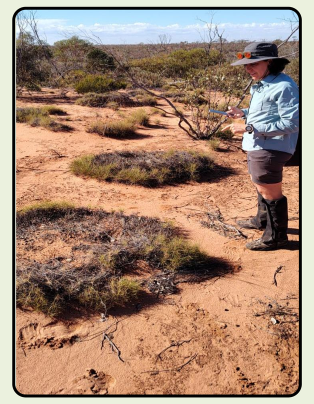
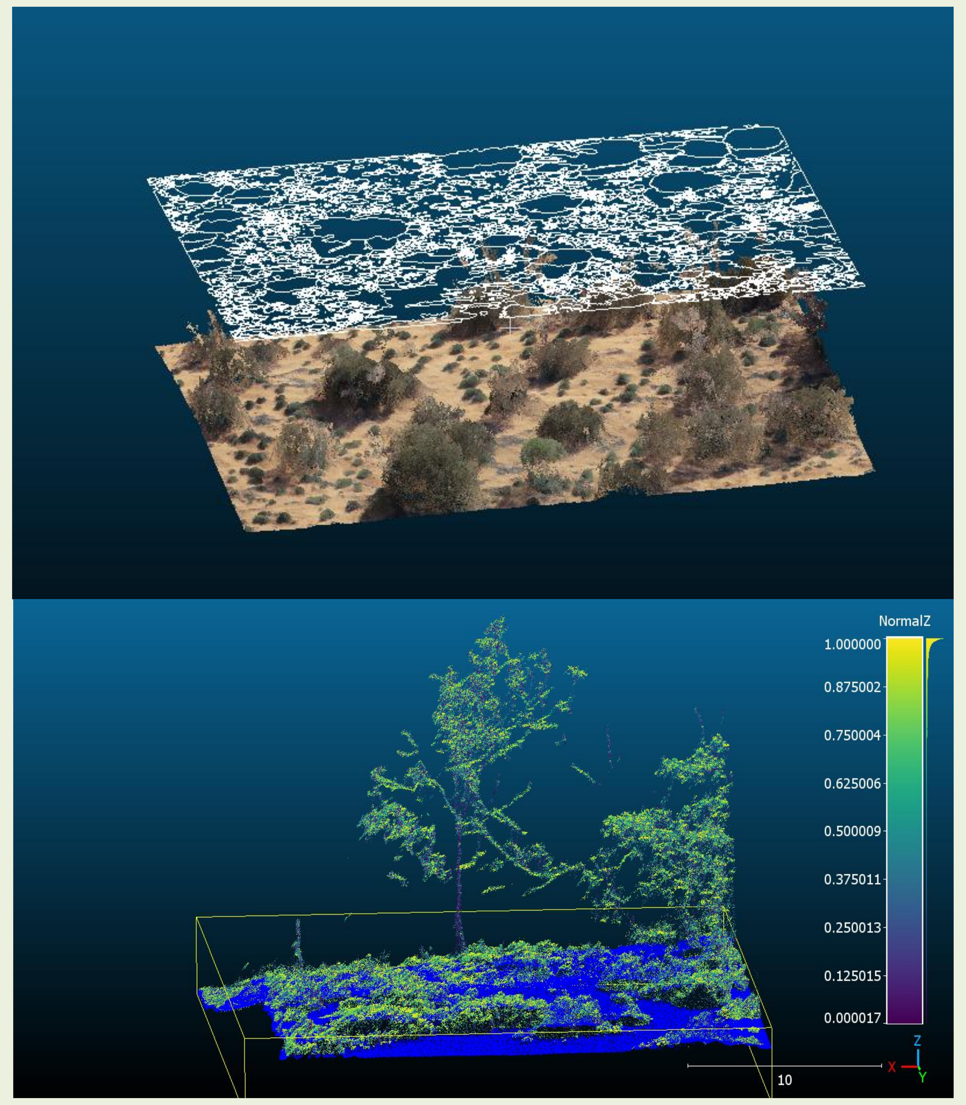
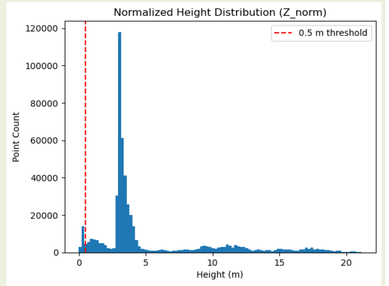


2_Automated preprocessing



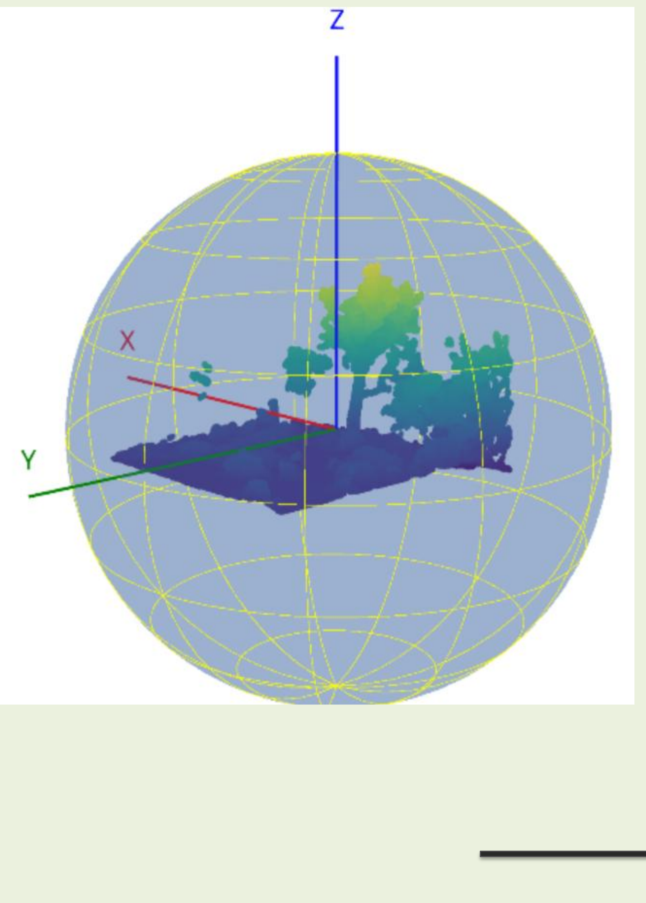
python

CloudCompare



COMPUTE:
- Clipping
- Cloth Simulation Filtering (CSF) for Ground Classification
- Normalise the Z values (heights) above ground based on minimum ground elevation

3_Voxelisation grid – structural representation

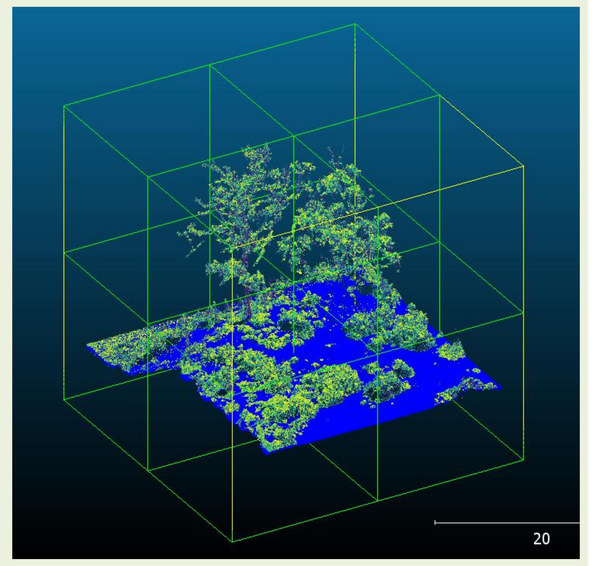


A) POLAR VOXEL GRID:
- r – Radial distance
- θ – Azimuthal angle (horizontal)
- ϕ – Elevation angle (vertical angle from Z-axis)

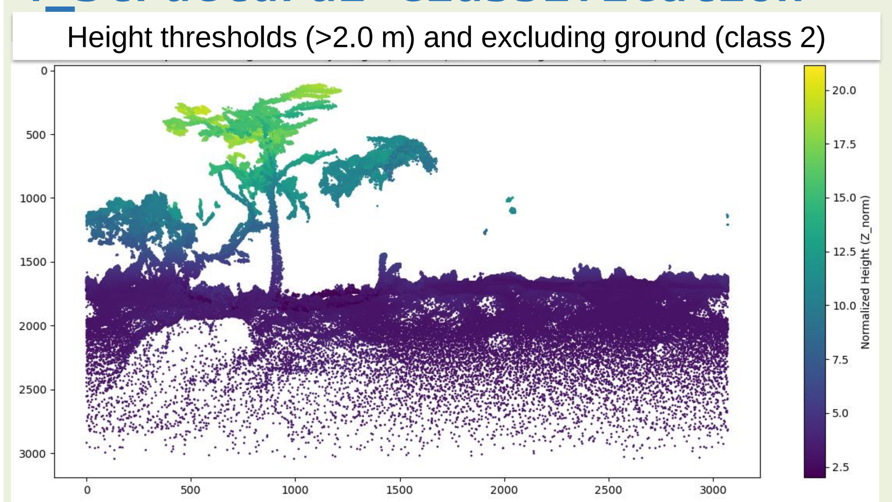
PURPOSE: enables modelling of radial and angular structure of vegetation such as plant symmetry, crown spread, and branching angles.

B) CARTESIAN VOXEL GRID:
- 3D grid along X, Y, Z directions

PURPOSES: enables mapping/semantic segmentation of vertical vegetation layers and estimation of vegetation volume using stratified voxel labels (e.g., herbaceous, shrub, canopy)

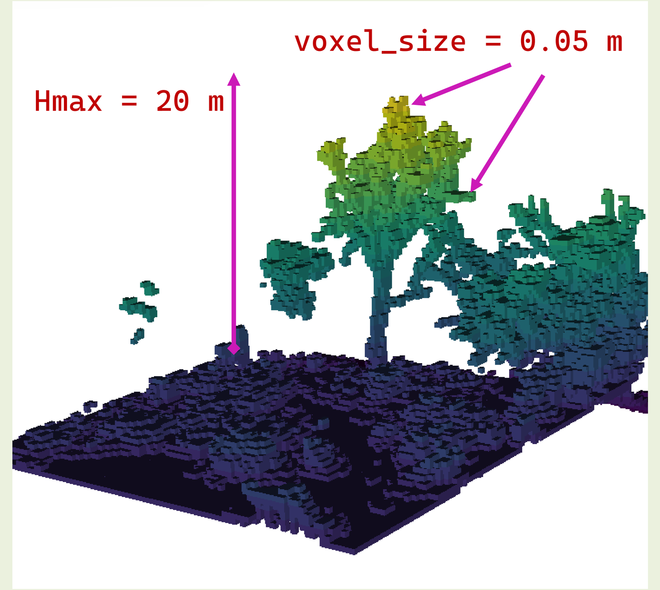


4_Structural Classification



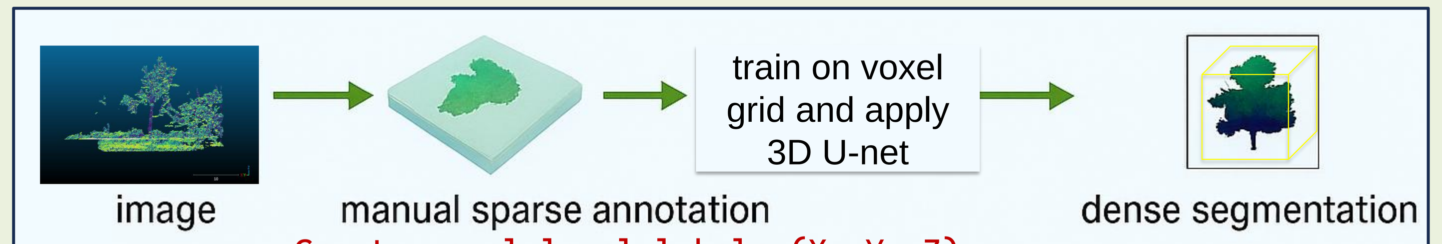
2. COMPUTE:
- Voxel statistics = mean normalised height per voxel
- Z slices = $\frac{H_{max}}{H_{voxel}}$=320
- Z slices compressed

1. FILTER:
- Ground points (e.g., class 2 after CSF)
- Apply height threshold
- Create stratification based on z_norm
- Assign points into (X, Y, Z) voxel grid based on spatial and vertical position



5_Tensor preparation – Deep Learning

PyTorch



Create voxel-level labels (X, Y, Z)

(C, X, Y, Z)
(6 channel,128×128 spatial,320 vertical slices)

(X, Y, Z)
(3 classes, X, Y, 320)

(X,Y,Z) = (128,128,320)

1. 3D INPUT (VOXEL CUBE):
4D array with dimensions

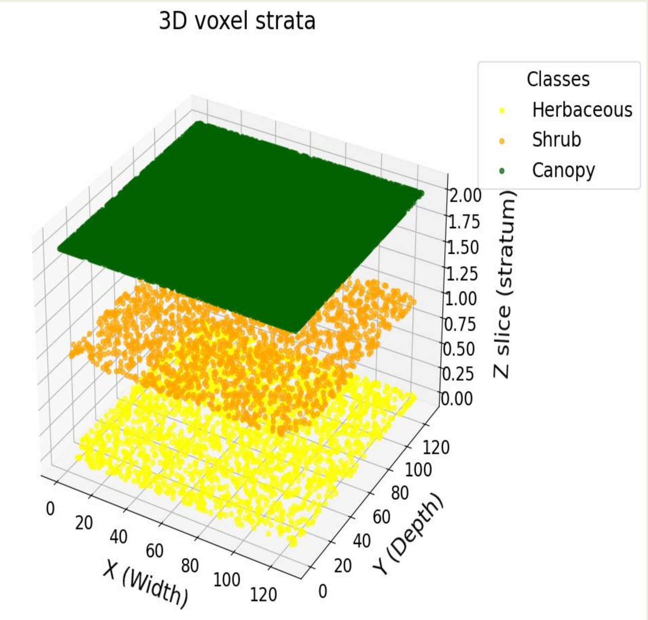
1) C – 6 Channels (features information per voxel):
--spectral: 5 Multispectral bands
--structural: 1 voxel norm_height stats (mean normalized height inside that voxel.)

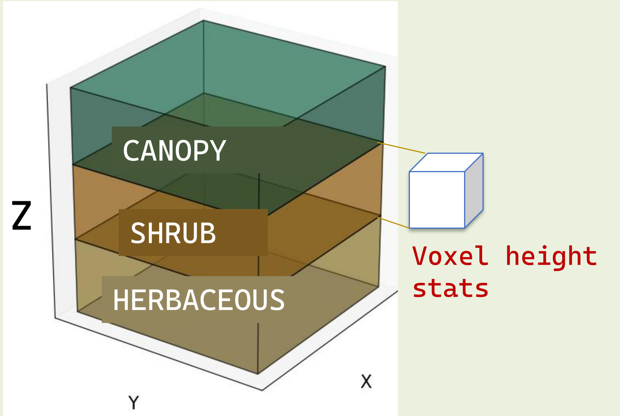
2) X – Width
3) Y – Depth

Horizontal (spatial/grid voxel size)

4) Z slice – Height (Vertical above ground/ voxel vertical position layers)

2. GROUND TRUTH:
Each voxel stores a class label (1, 2, or 3)





3. 3D convolutions learn spatial and vertical structure of vegetation strata:
- Horizontal shape (X, Y)
- Vertical height (Z) or angular (r, θ, ϕ)