

LARIAC Case Study

Optimizing the Planning and Management of Los Angeles County's Urban Forest

Funders + Advisors + Collaborators

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Urban Forest Planning & Management

Los Angeles County faces public health challenges due to:

- Changing climate,
- Increased drought, and
- Natural disasters like fire.

Optimizing the planning and management of the urban forest using remote sensing can help determine which species are responding better to these challenges.

There are eight County departments responsible for public trees, and traditional methods for conducting tree inventories are resource-intensive.



Project Goals

Identify individual urban tree species from aerial imagery and derive canopy metrics over time across our pilot sites

- Using these results, determining the tree's health status becomes a welcomed future application

Assist stakeholders, who are manage urban forest stock manually, to deploy their expertise more efficiently and save time

Stakeholder Engagement

To ensure our project goals are met, we sought input from stakeholders in early 2021 to identify the needs and priorities of those that will be using our product in day-to-day operations:

- **Stakeholder Advisory Group**
 - Users from within and outside the County
- **Technical Advisory Group**
 - A small group of field experts to advise on the technical aspects

Review of Stakeholder Objectives

In order to prioritize the workflow of our model, stakeholder input is a crucial step needed to identify existing operational issues in regional urban forest management and set the top priorities for our pilot project:

- **Individual tree species identification**
- **Canopy cover metrics**
- **Health assessment**



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Selected 11 target species/Genera:

- Four native
- Seven non-native

- Potential planting sites

Review of Stakeholder Objectives

Selected tree species/Genera chosen for our pilot sites:

Non-native

Orange (*Citrus* spp)

Crepe Myrtle (*Lagerstroemia* spp)

Eucalyptus (*Eucalyptus* spp)

Jacaranda (*Jacaranda mimosifolia*)

Pines (*Pinus* spp)

Figs (*Ficus* spp)

Palms (*Washingtonia* spp)

Native

Coast Live Oak (*Quercus agrifolia*)

California Sycamore (*Platanus racemosa*)

Coast Redwood (*Sequoia sempervirens*)

California Walnut (*Juglans californica*)

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Metrics shared that are important for user's day-to-day operations:

- Crown area per species / individual trees
- Crown spread
- Canopy change over time

Review of Stakeholder Objectives

In order to prioritize the workflow of our model, stakeholder input is a crucial step needed to identify existing operational issues in regional urban forest management and set the top priorities for our pilot project:

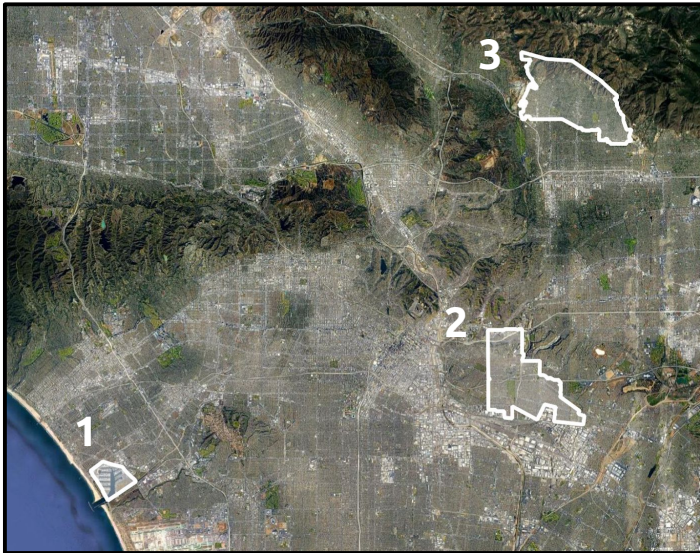
- **Individual tree species identification**
- **Canopy cover metrics**
- **Health assessment**

Metrics that are important for user's day-to-day operations:

- Tree condition

Pilot Sites

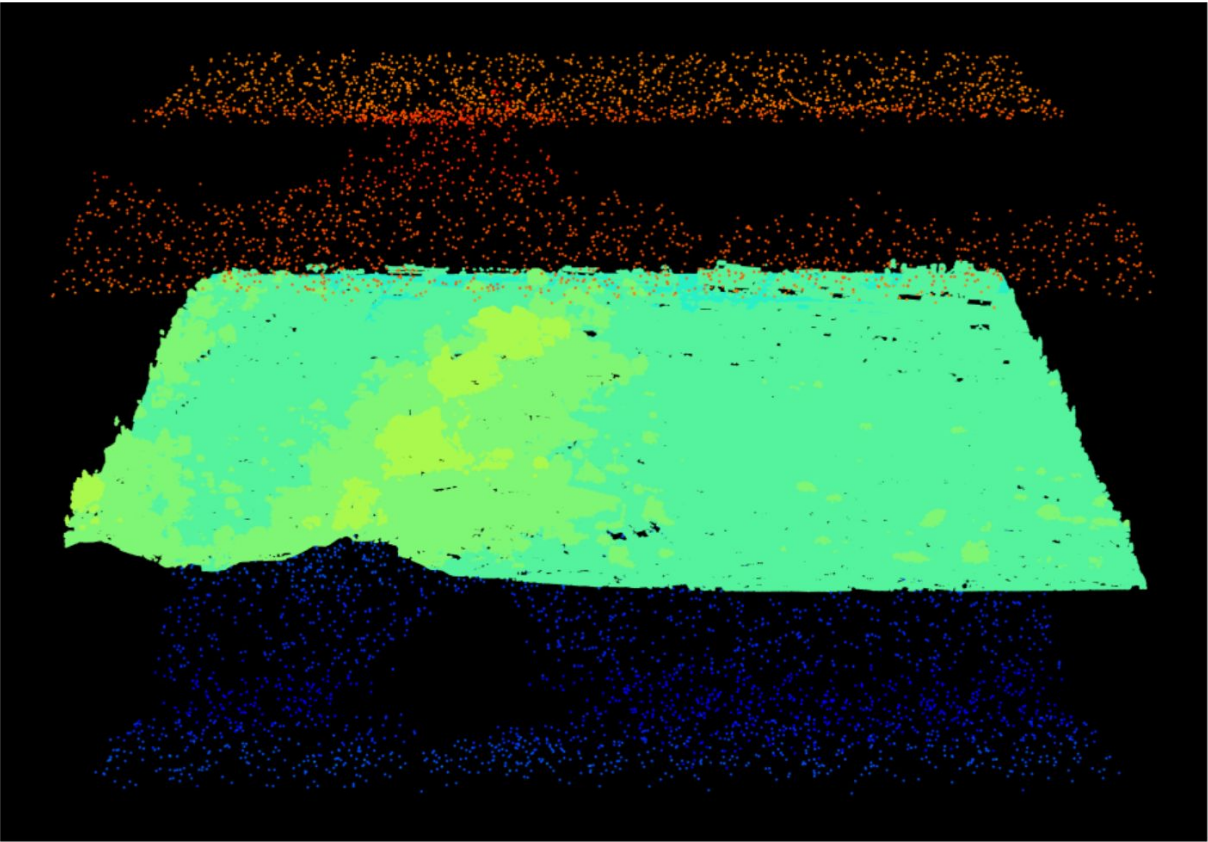
Prior to scaling to the entire county, we plan to test our models across three diverse, unincorporated areas in urban LA County. We chose these locations due to their diversity in tree species, demographics, and management approaches:



1. **Marina del Rey**
2. **East Los Angeles**
3. **Altadena**

Data Processing:

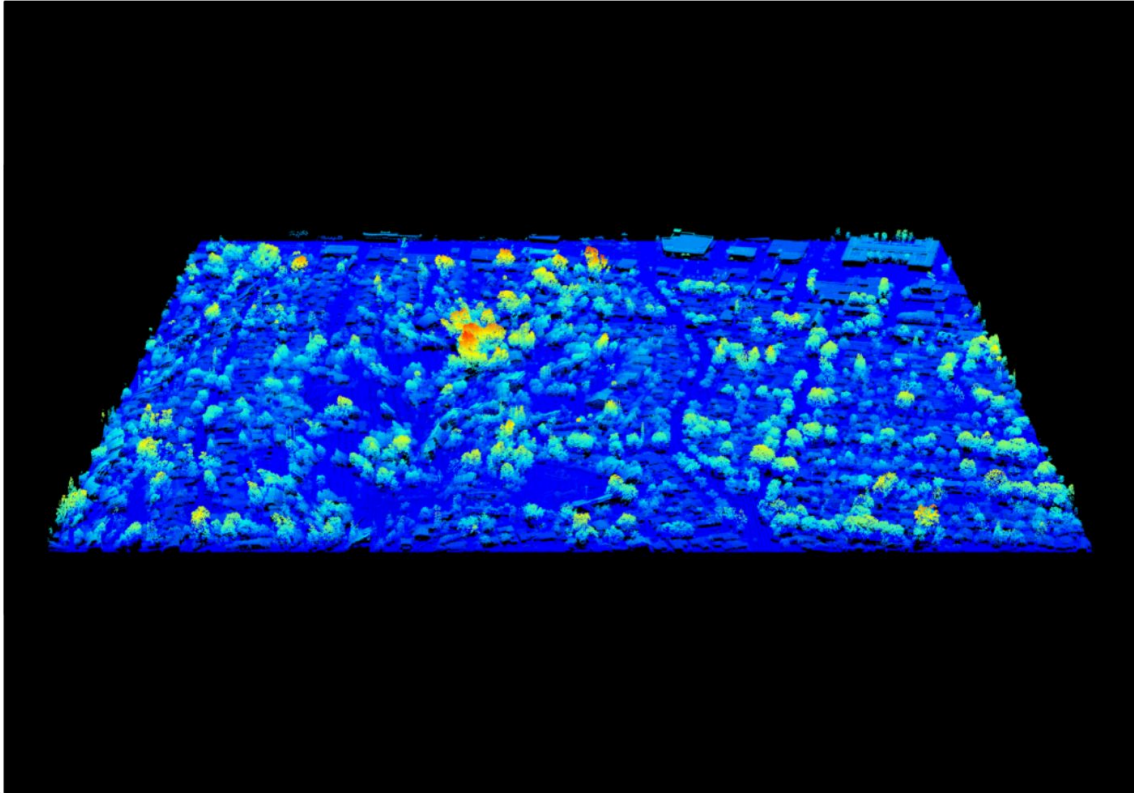
Processing tile-by-tile.



Raw version of LARIAC 4 tile with below- and above-ground noise and topography.

Data Processing:

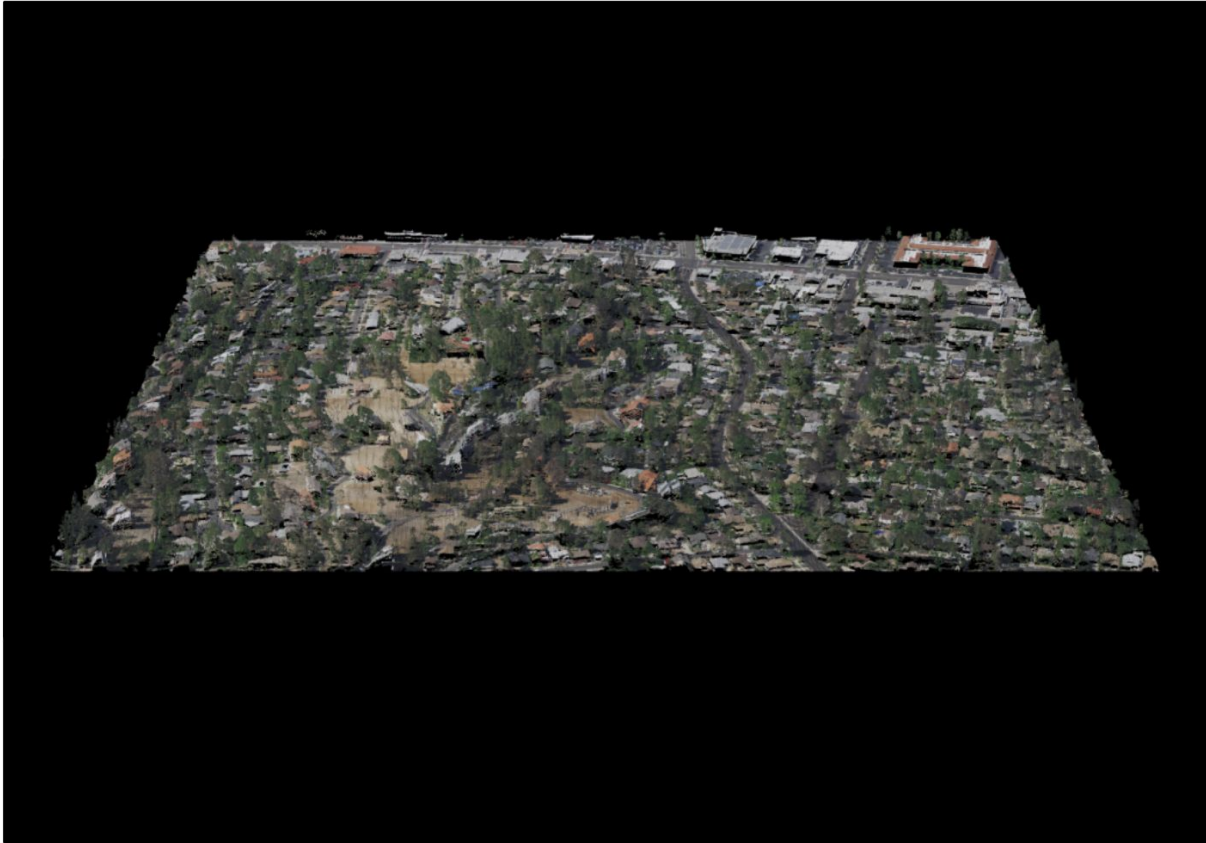
Processing tile-by-tile.



1. Normalizing the topography, a.k.a. setting the ground to '0'
2. Filtering for height: $0 \leq Z < 220$ ft (corrects for below-ground noise)
3. Selecting points inside the 90th percentile of height (corrects for above-ground noise)

Data Processing:

Processing tile-by-tile.

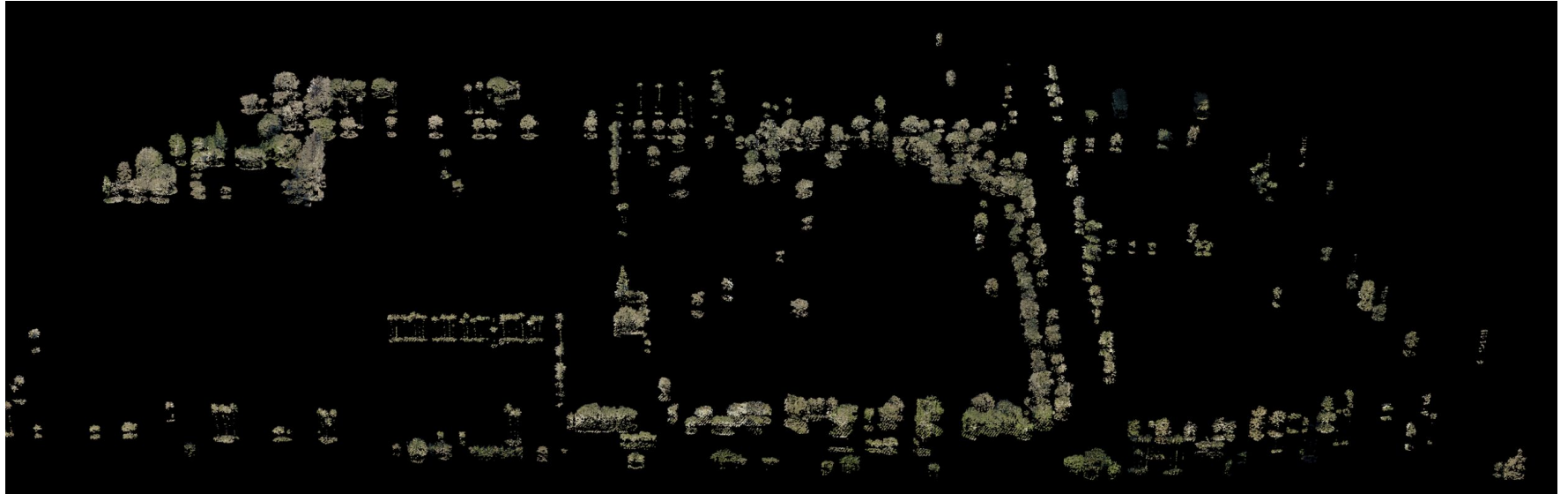


Merging (draping) NAIP digital numbers with point-cloud.

UCLA College | Social Sciences
Geography

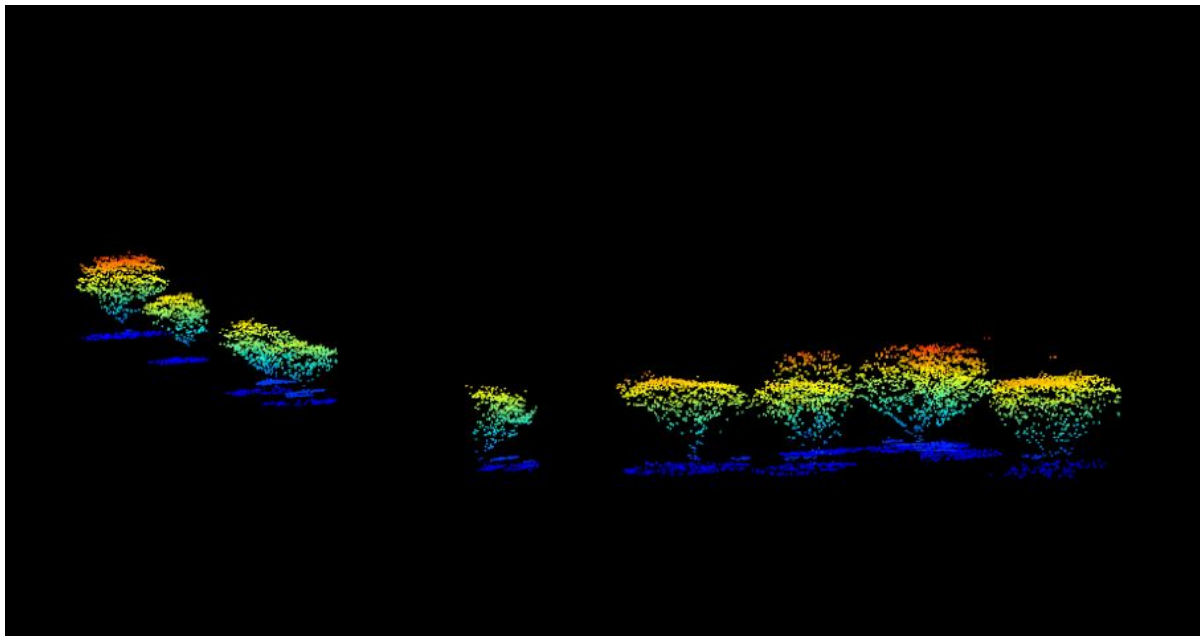


Tree Mask



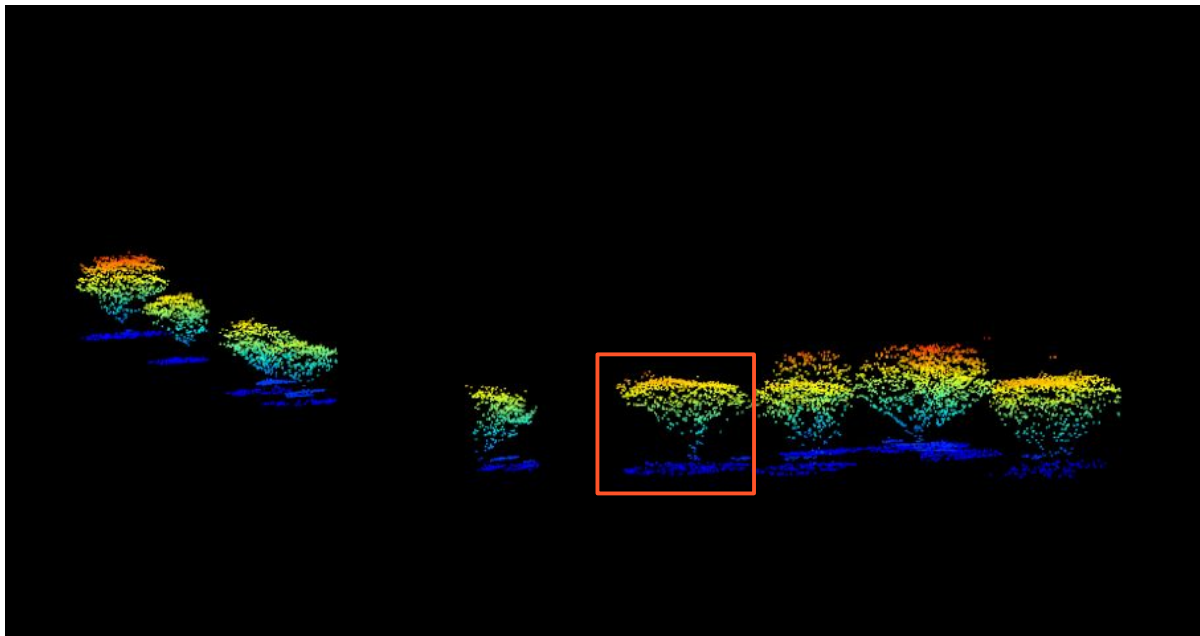
Tree Canopy Layer derived from LARIAC Land Cover (2016) - Example from Marina del Rey

Tree Segmentation



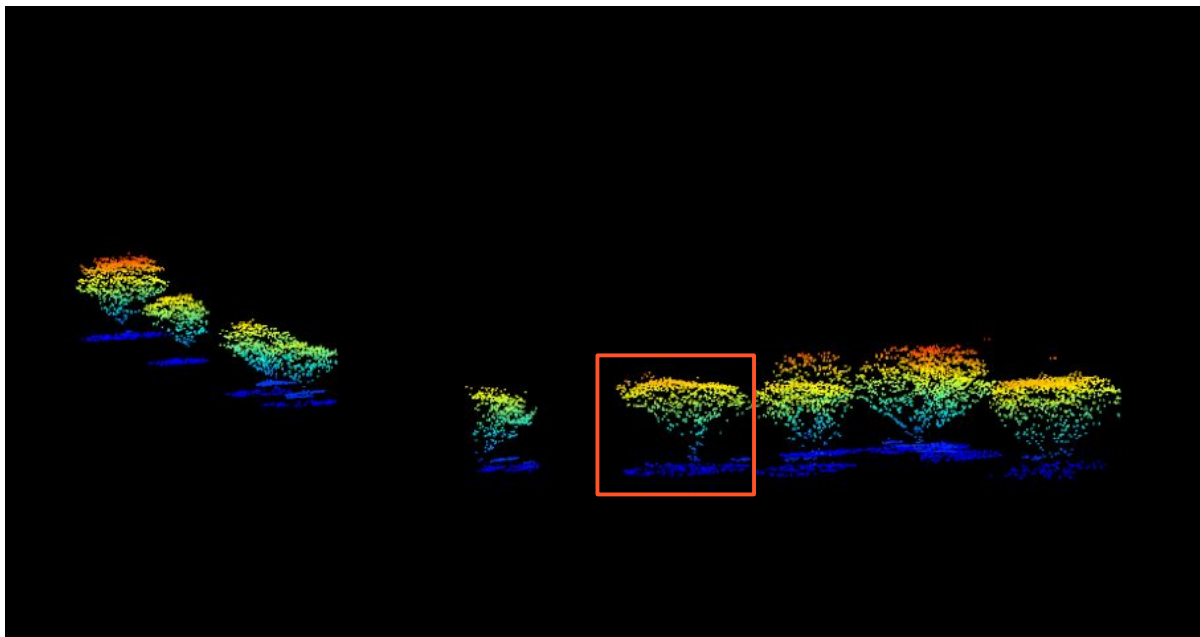
Erythrina caffra (not a target species) from Marina del Rey.

Single Tree ID

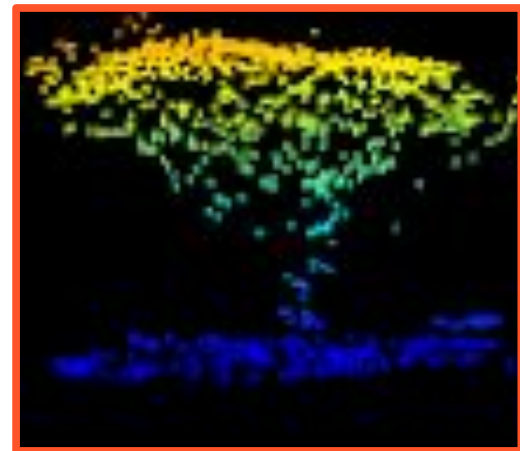


Erythrina caffra (not a target species) from Marina del Rey.

Single Tree Segmentation

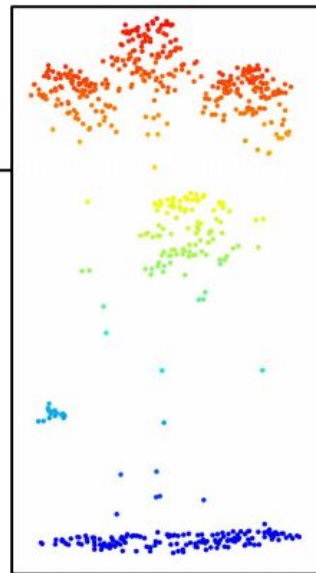


Erythrina caffra (not a target species) from Marina del Rey.



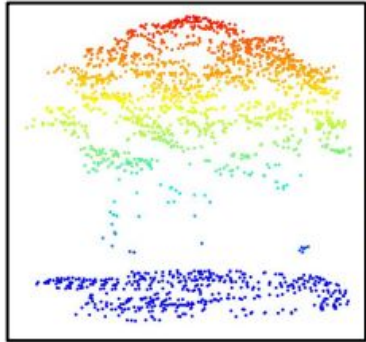


*Washingtonia
robusta*

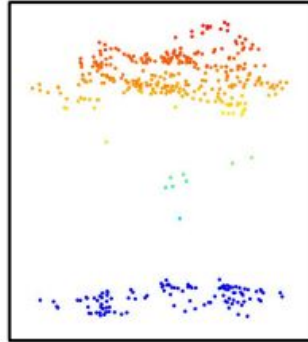




Ficus spp.



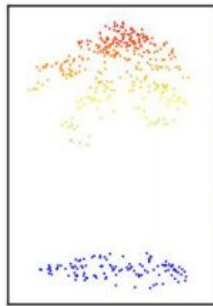
Ficus rubiginosa



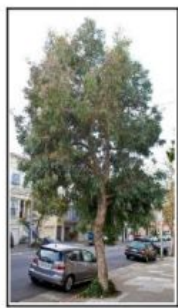
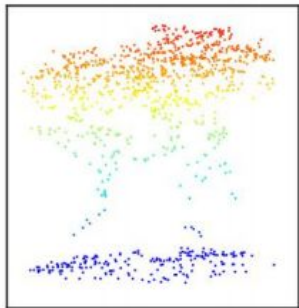
Ficus microcarpa 'nitida'



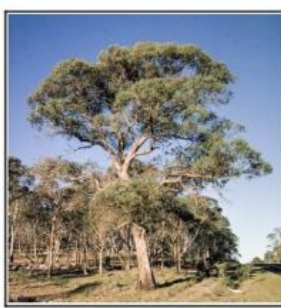
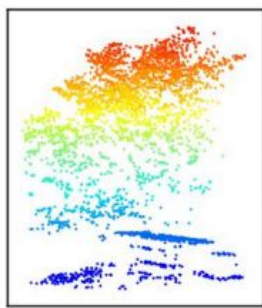
Eucalyptus sideroxylon



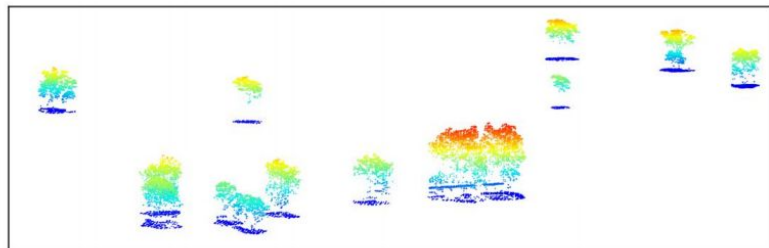
Eucalyptus citriodora



Eucalyptus polyanthemus



Eucalyptus nicholii



Eucalyptus spp.

Sample of Crown Metrics

Group	Num of Crowns	Mean Density (N pts)	Mean Height (ft)	Mean Area (sq ft)	Mean Perim (ft)
<i>Citrus spp</i>	506	209.68	28.59	879.96	102.16
<i>Eucalyptus spp</i>	3713	362.01	43.06	1170.66	118.5
<i>Ficus spp</i>	8707	460.84	32.94	1479.86	130.7
<i>Jacaranda mimosifolia</i>	2504	399.16	33.38	1277.15	122.79
<i>Juglans californica</i>	330	219.53	35.95	1008.08	110.18
<i>Lagerstroemia spp</i>	10558	151.53	23.91	707.15	90.28
<i>Pinus spp</i>	9952	248.04	55.83	937.32	105.44
<i>Platanus racemosa</i>	1518	341.21	46.99	1017.41	109.95
<i>Quercus agrifolia</i>	2165	407.52	36.94	1442.74	130.73
<i>Sequoia sempervirens</i>	330	216.81	54.03	799.23	97.69
<i>Washingtonia spp</i>	9152	184.87	60.41	664.34	89.06

Species Highlight: California Natives





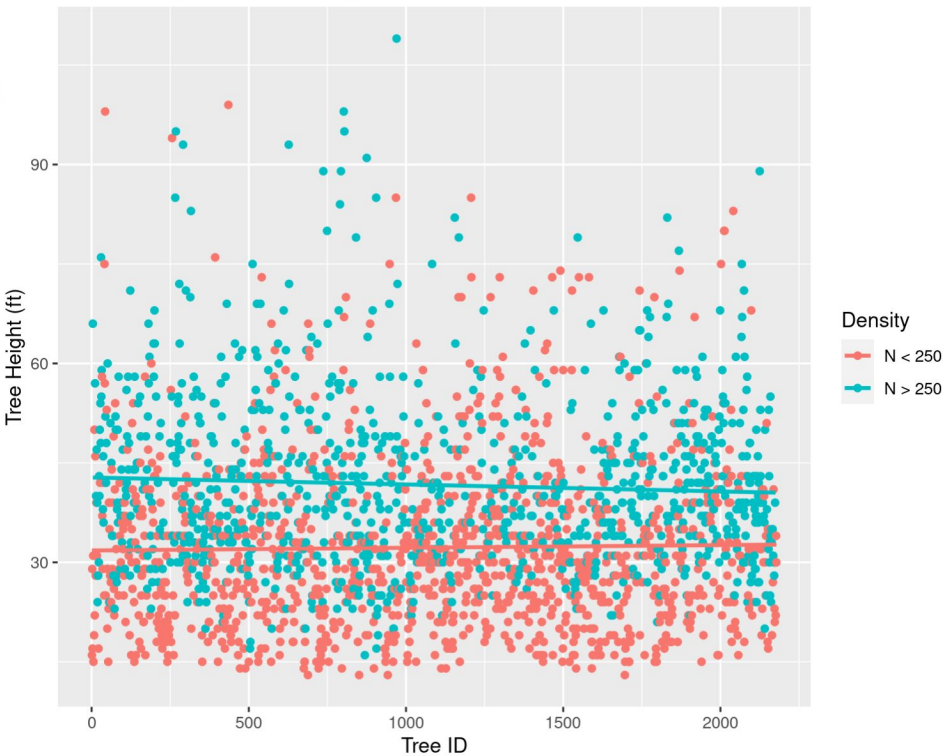
Black walnut <i>Juglans californica</i>	Coastal live oak <i>Quercus agrifolia</i>	Coastal redwood <i>Sequoia sempervirens</i>	California sycamore <i>Platanus racemosa</i>
Deciduous	Deciduous	Conifer	Deciduous
			

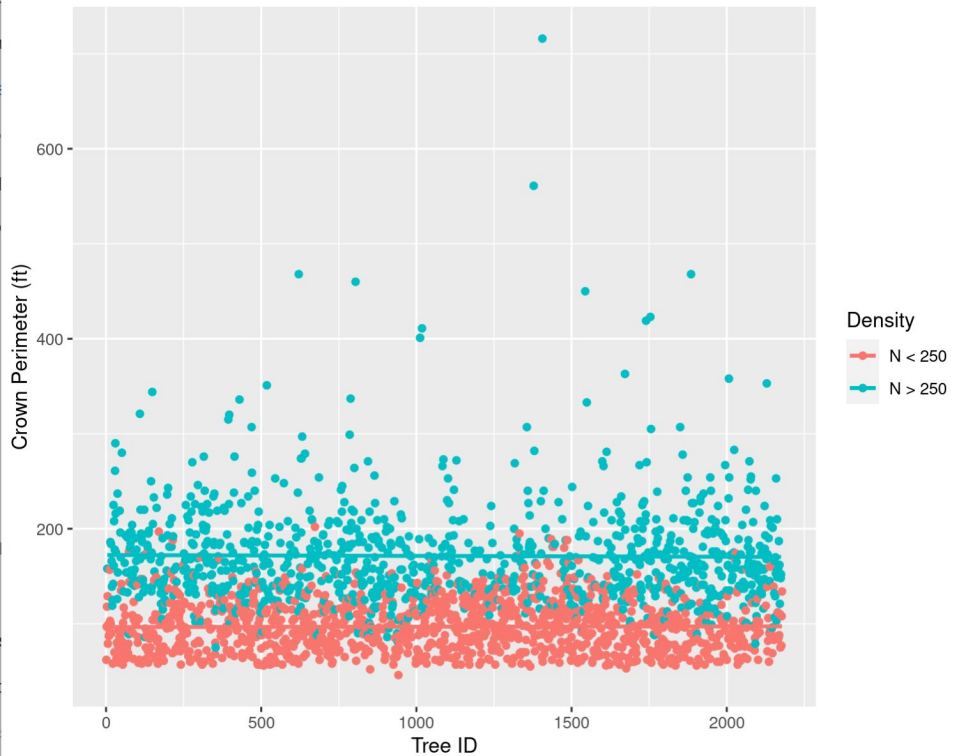
Table produced by Kristi Le

Crown Metrics: *Quercus agrifolia*

Quercus agrifolia Tree Height



Quercus agrifolia Perimeter



Proxy Health Assessment: Satellite NDVI

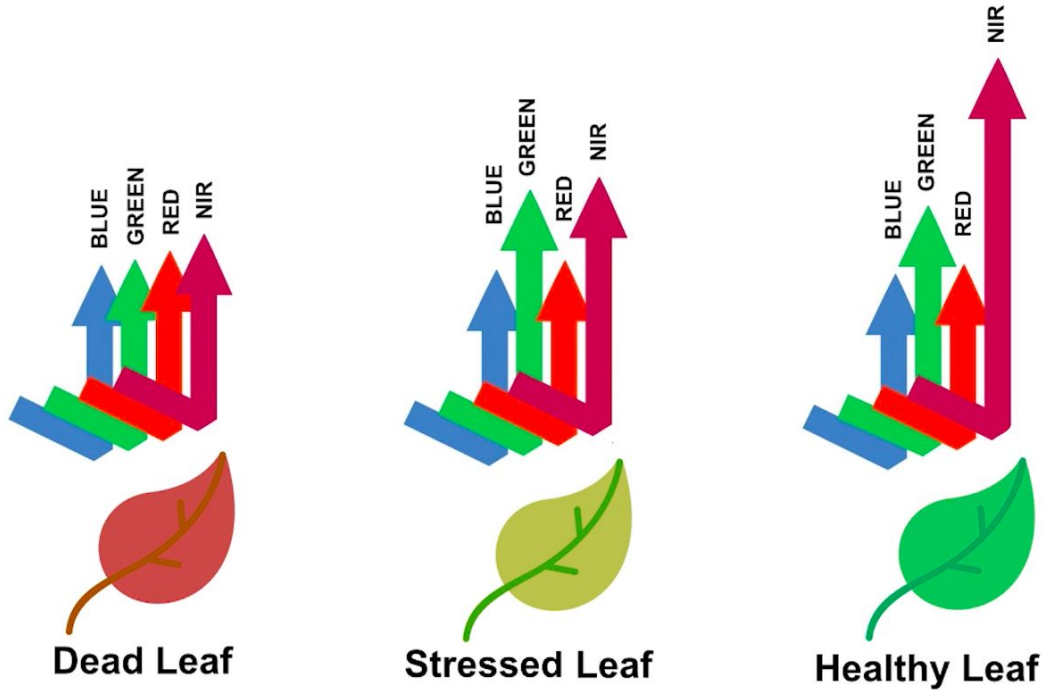


Image source: *regrow*

$$\text{NDVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}}$$



Sentinel-2 satellite constellation
Repeat observations every 5 days
Image source: *European Space Agency*

Prevalence of Clouds - Sentinel-2 NDVI

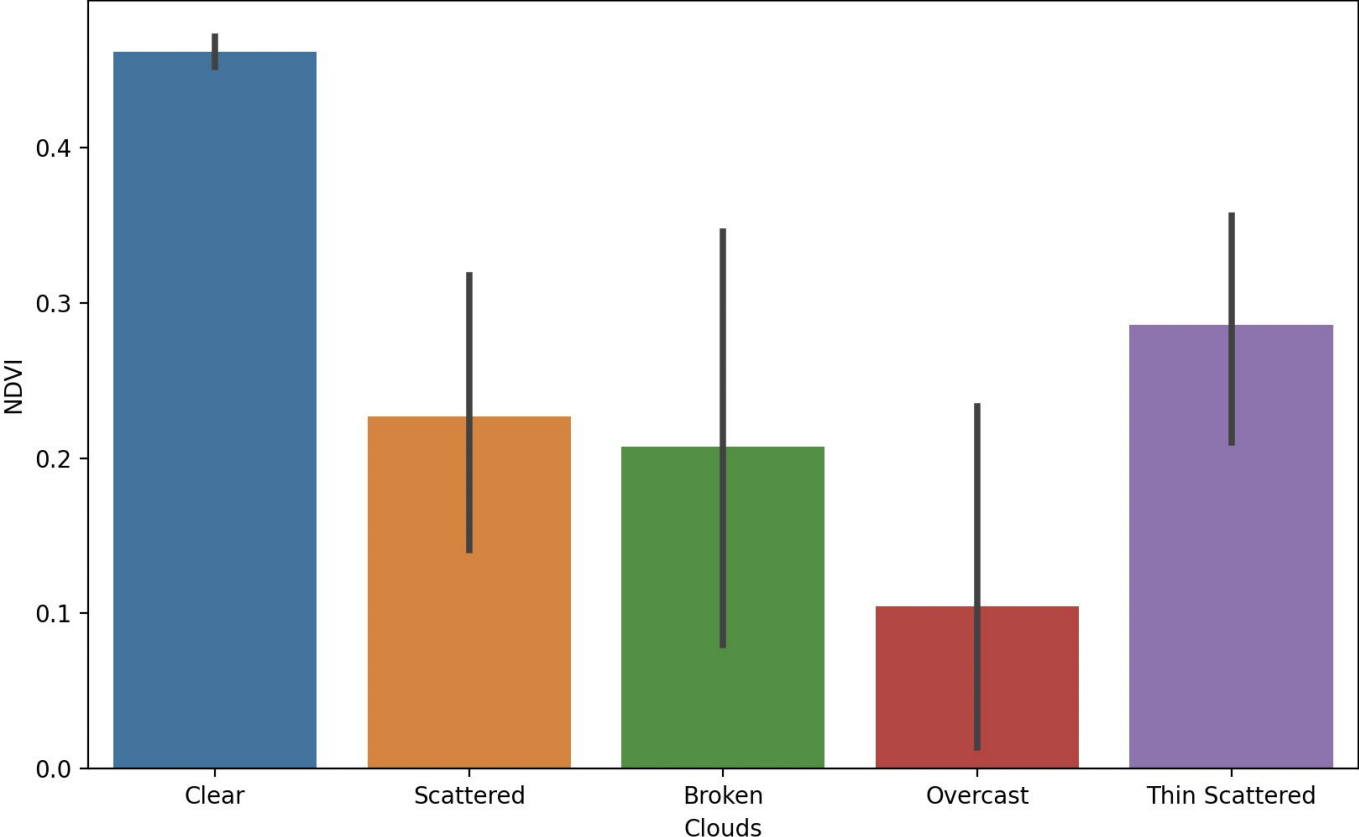


Chart produced by Kristi Le

Juglans californica (Sentinel-2)

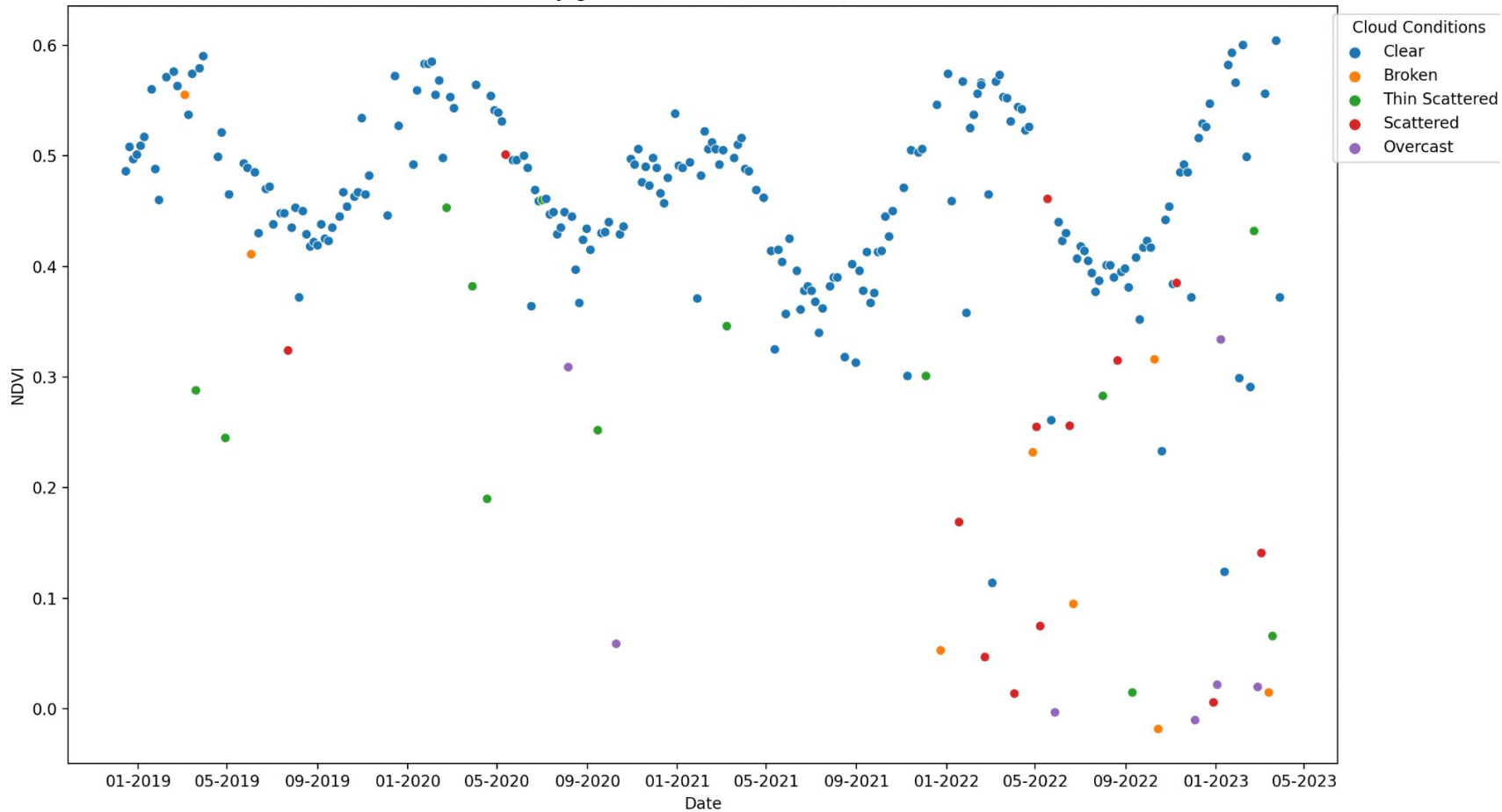


Chart produced by Kristi Le

Black walnut Sentinel-2 NDVI for Clear Days

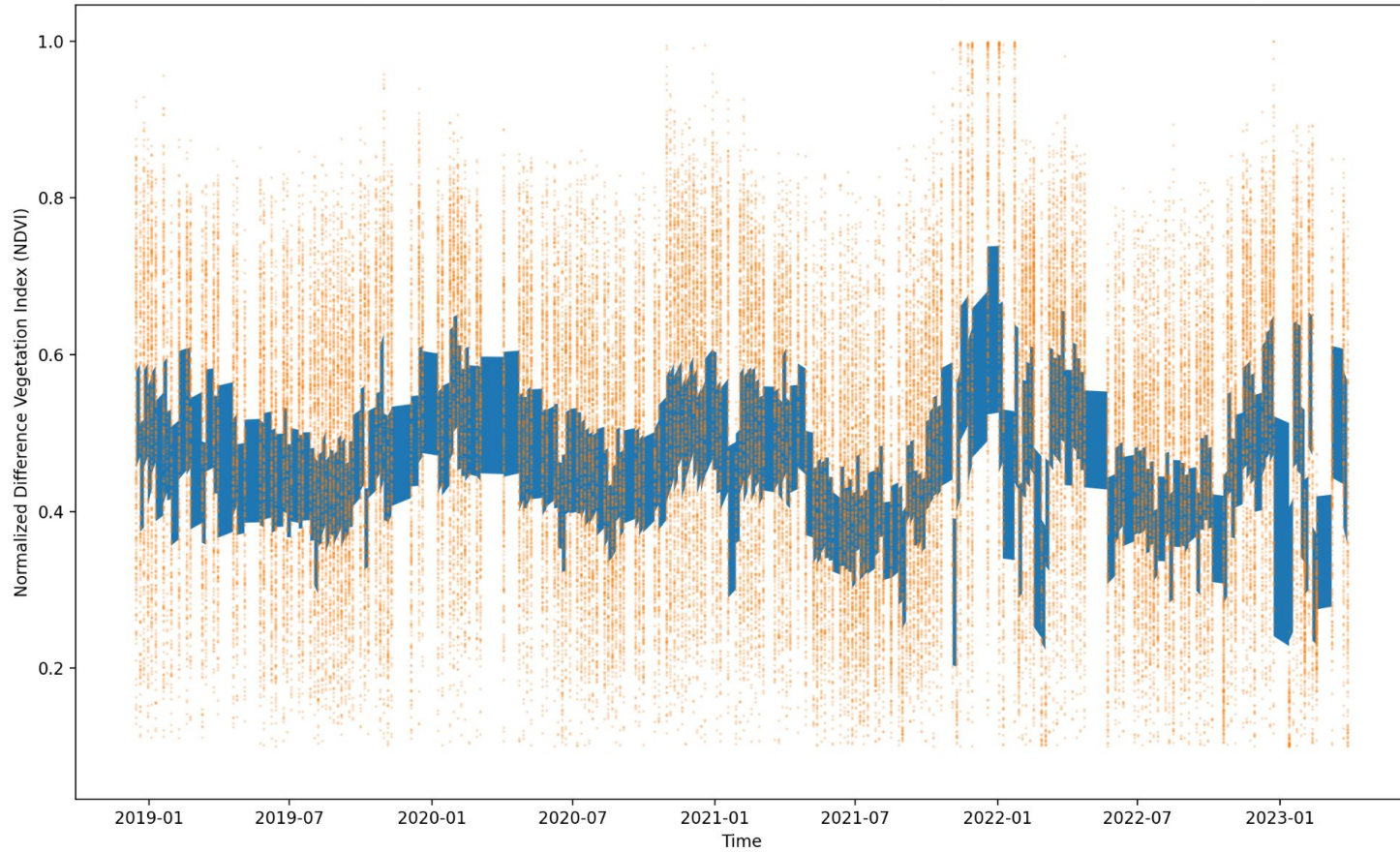


Chart produced by Kristi Le

Black walnut Sentinel-2 NDVI for Clear Days

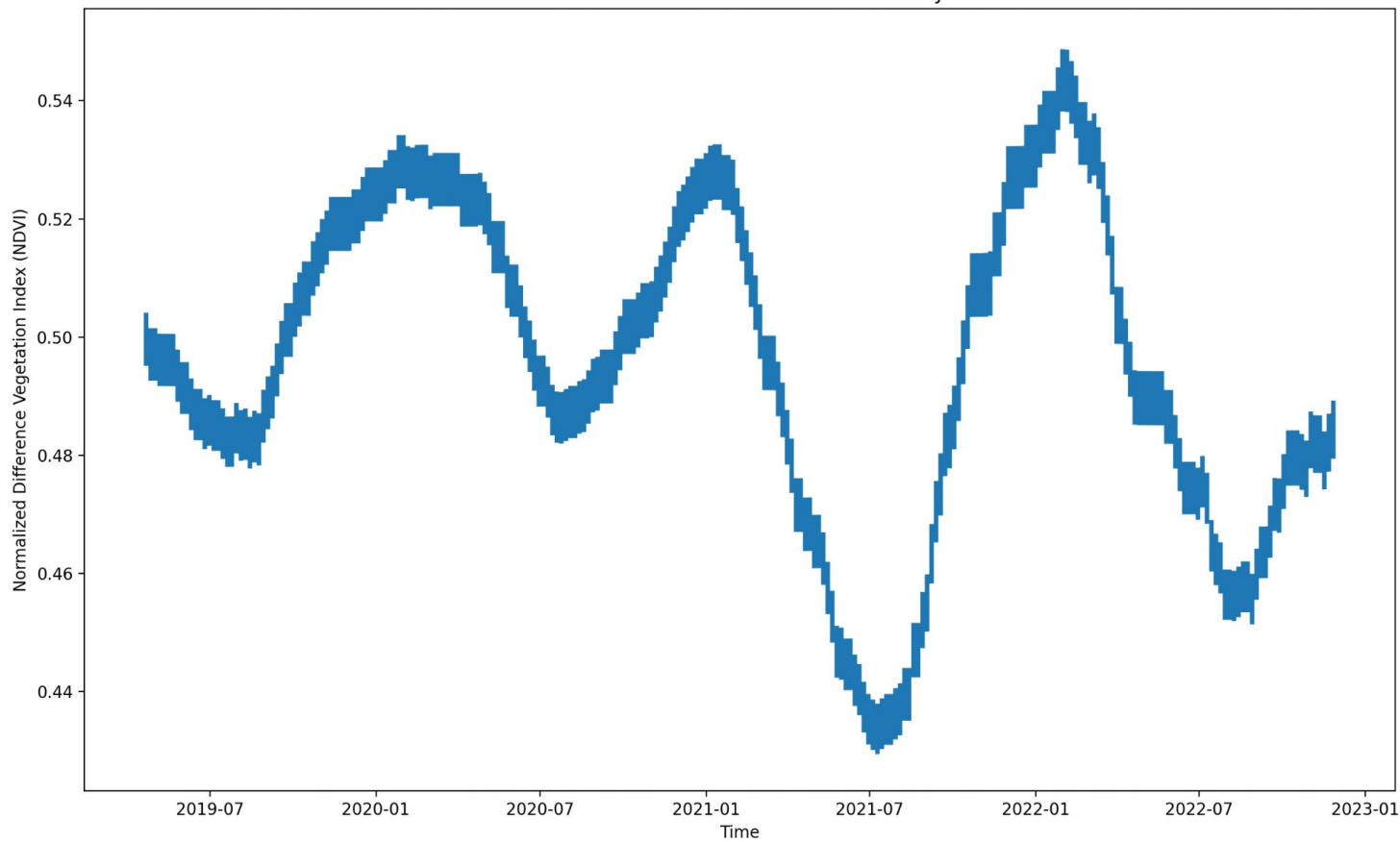


Chart produced by Kristi Le

NDVI Ranges for individual *Juglans californica*

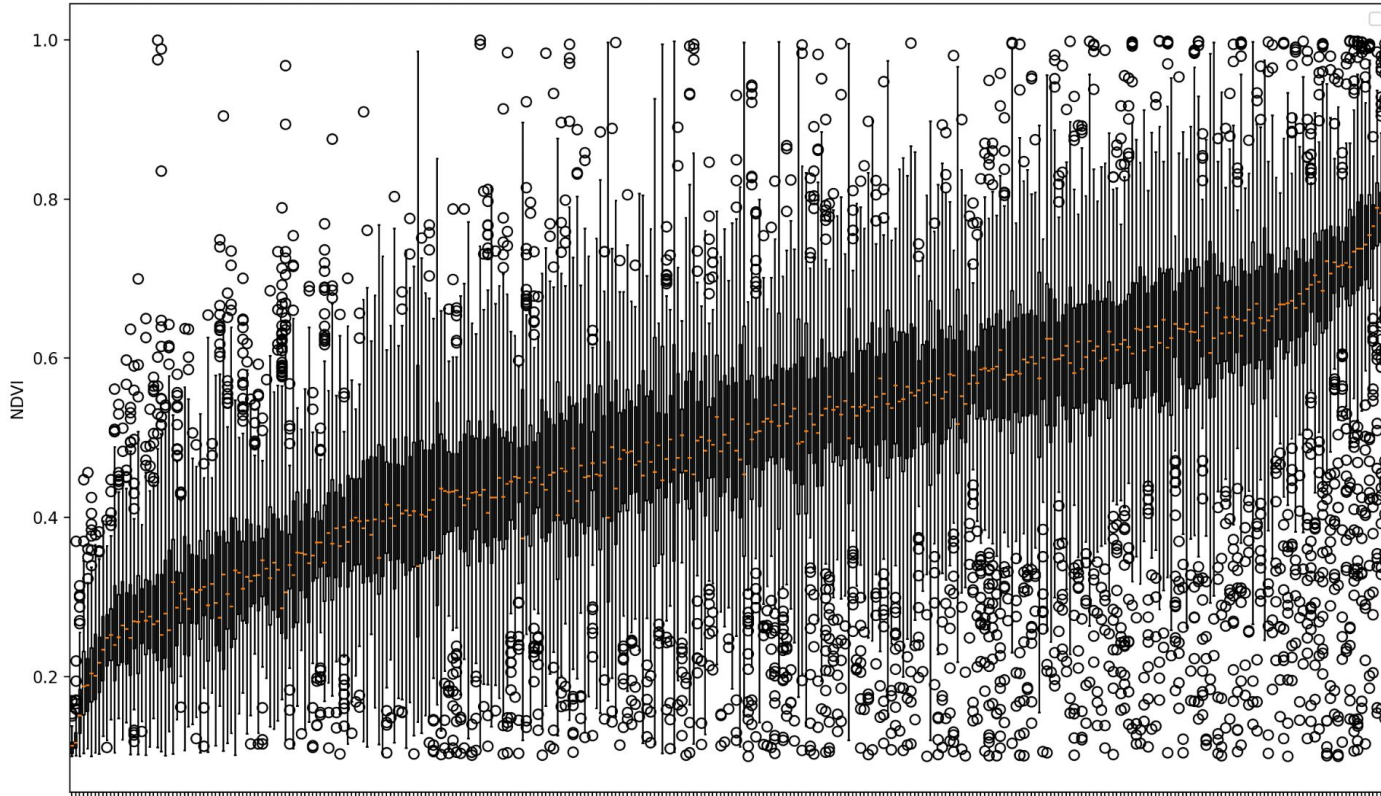
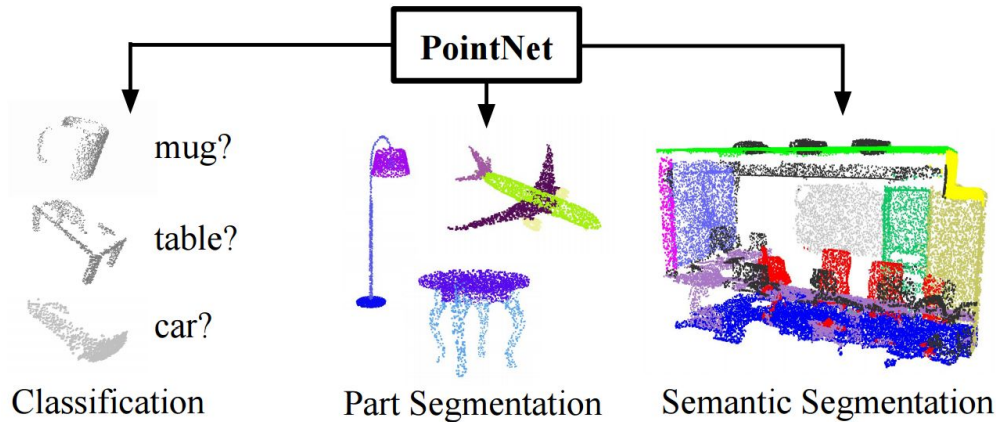


Chart produced by Kristi Le

3D Fully Convolutional Neural Network

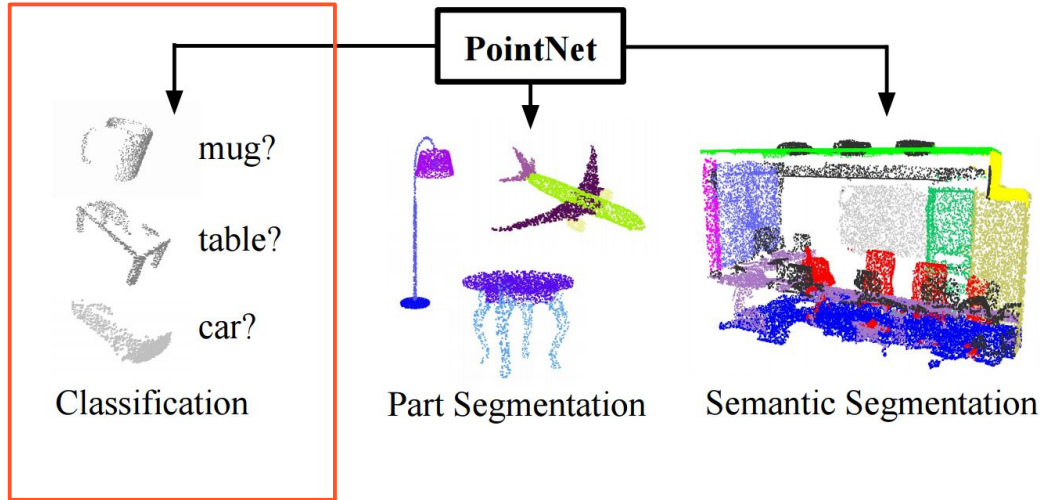


Originally made to classify and segments objects of interest in 3-D point clouds.

We engage in transfer learning to apply to tree species classification using aerial LiDAR.

Figure source: Qi et al. 2017

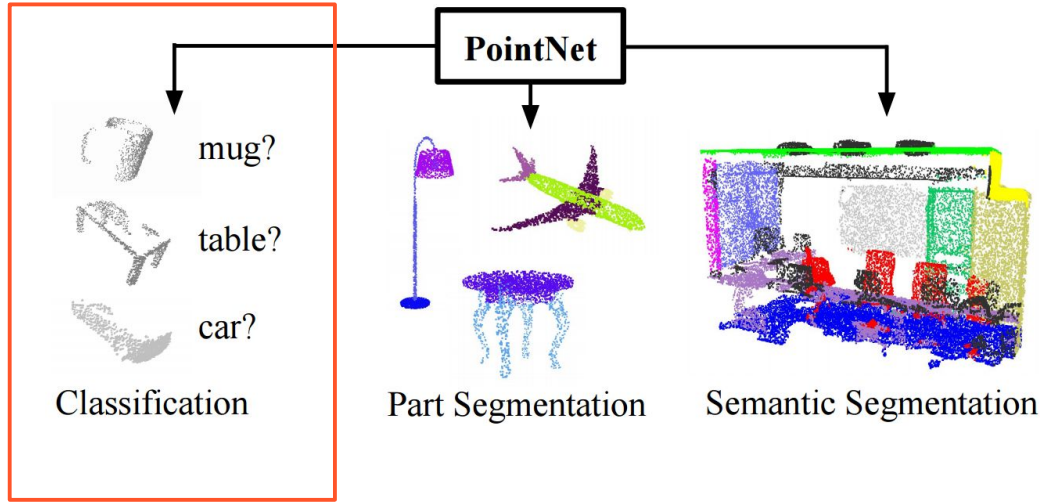
3D Fully Convolutional Neural Network



Randomly select 128 points per tree to create a uniform object to input into the PointNet architecture.

Classification based on structure (X, Y, Z) and reflectance (NIR, R, G)

Point Cloud Classification



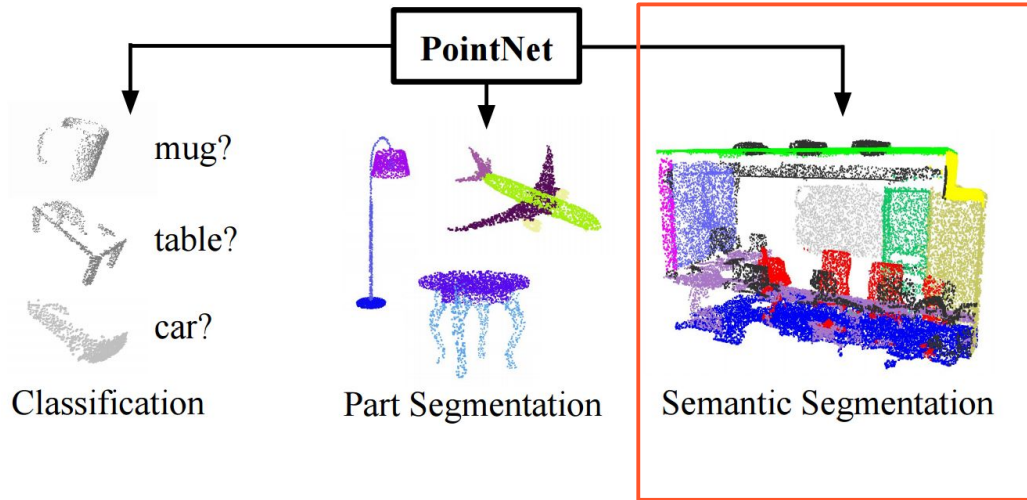
Results for our target species were not ideal:

~20% accuracy for individual species

~40% accuracy when grouped by structural similarity

~60% accuracy when grouped by structural & reflective similarity

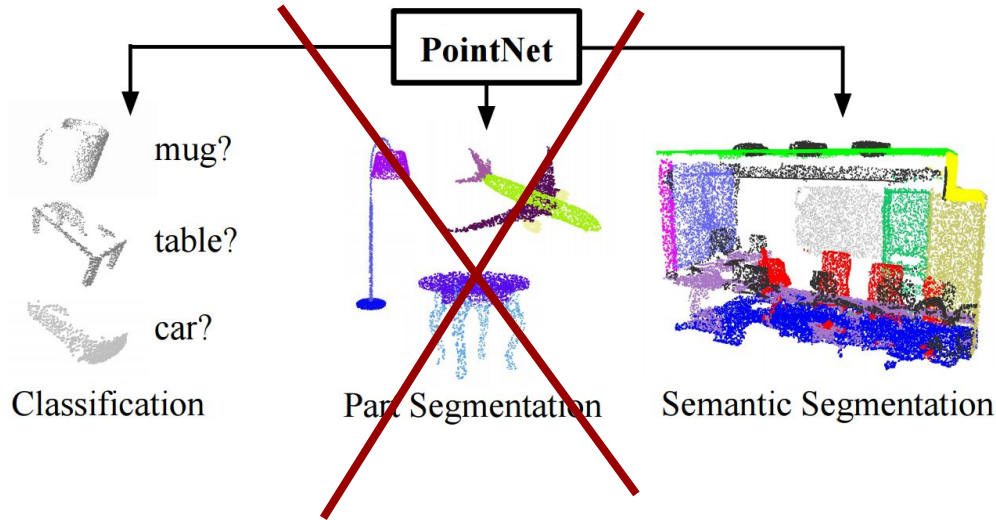
3D Fully Convolutional Neural Network



Feeding the model entire LiDAR scenes ($\frac{1}{4}$ - $\frac{1}{2}$ mile grids), and segmenting for target trees based on previously classified scenes.

Classification is still based on structure (X, Y, Z) and reflectance (NIR, R, G)

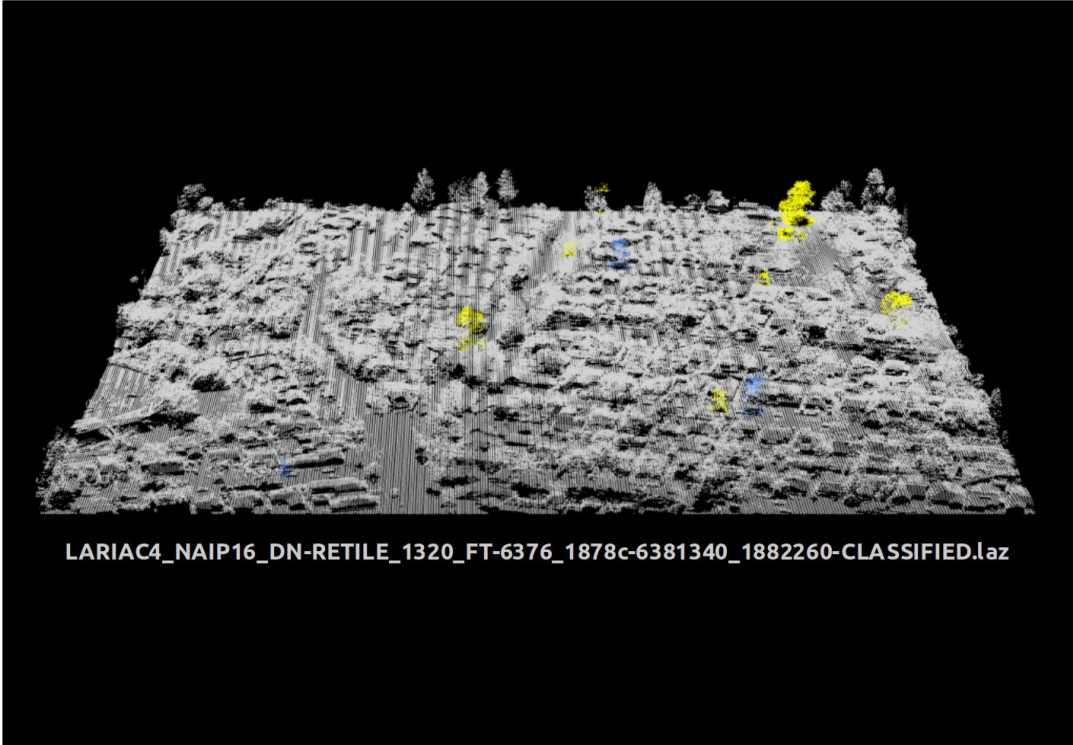
3D Fully Convolutional Neural Network



We do not need PointNet's part segmentation, since we are not looking to separate our target species into parts (i.e. branch, canopy, stem, etc.)

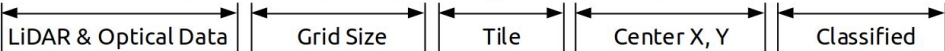
Data Processing:

Processing gridded scenes for semantic parsing.



Grid-naming Scheme:

LARIAC4_NAIP16_DN-RETILE_1320_FT-6376_1878c-6381340_1882260-CLASSIFIED.laz



Data Structure:

Attributes used in scene semantic parsing.

```
las S4 [743476 x 20] (lidR::LAS) S4 object of class LAS
└─ data list [743476 x 20] (S3: data.table) A data.table with 743476 rows and 20 columns
  X double [743476] 6363520 6363520 6363520 6363520 6363520 6363520 ...
  Y double [743476] 1898704 1898705 1898712 1898712 1898727 1898734 ...
  Z double [743476] 18.9 19.1 22.5 22.7 20.8 17.5 ...
  gpstime double [743476] 0 0 0 0 0 ...
  Intensity integer [743476] 0 0 0 0 0 ...
  ReturnNumber integer [743476] 1 1 1 1 1 1 ...
  NumberOfReturns integer [743476] 1 1 1 1 1 1 ...
  ScanDirectionFlag integer [743476] 0 0 0 0 0 ...
  EdgeOfFlightline integer [743476] 0 0 0 0 0 ...
  Classification integer [743476] 0 0 0 0 0 ...
  Synthetic_flag logical [743476] FALSE FALSE FALSE FALSE FALSE ...
  Keypoint_flag logical [743476] FALSE FALSE FALSE FALSE FALSE ...
  Withheld_flag logical [743476] FALSE FALSE FALSE FALSE FALSE ...
  ScanAngleRank integer [743476] 0 0 0 0 0 ...
  UserData integer [743476] 0 0 0 0 0 ...
  PointSourceID integer [743476] 0 0 0 0 0 ...
  R integer [743476] 44461 44461 44461 45232 33924 32125 ...
  G integer [743476] 35723 35723 35466 35980 27499 27242 ...
  B integer [743476] 33667 33667 33410 33667 26985 26471 ...
  N integer [743476] 35209 35209 34952 37008 26471 25186 ...
```

1. Structure: X, Y, Z
2. Classification: 0, 'No species,' 1 – 31, 'Species name'
3. Spectral: R, G, B, N



Project Assessment

To best serve the needs of our stakeholders, we have to weigh the processing and computational needs of 3-D point cloud classification vs. other traditional forms of species classification using remote sensing.

Even if the **scene semantic parsing** yields better results than a raster-based classification (2-D), will the results be significant enough to justify the complex workflow?

Next Stakeholder meeting: May, 31

Thank you!

