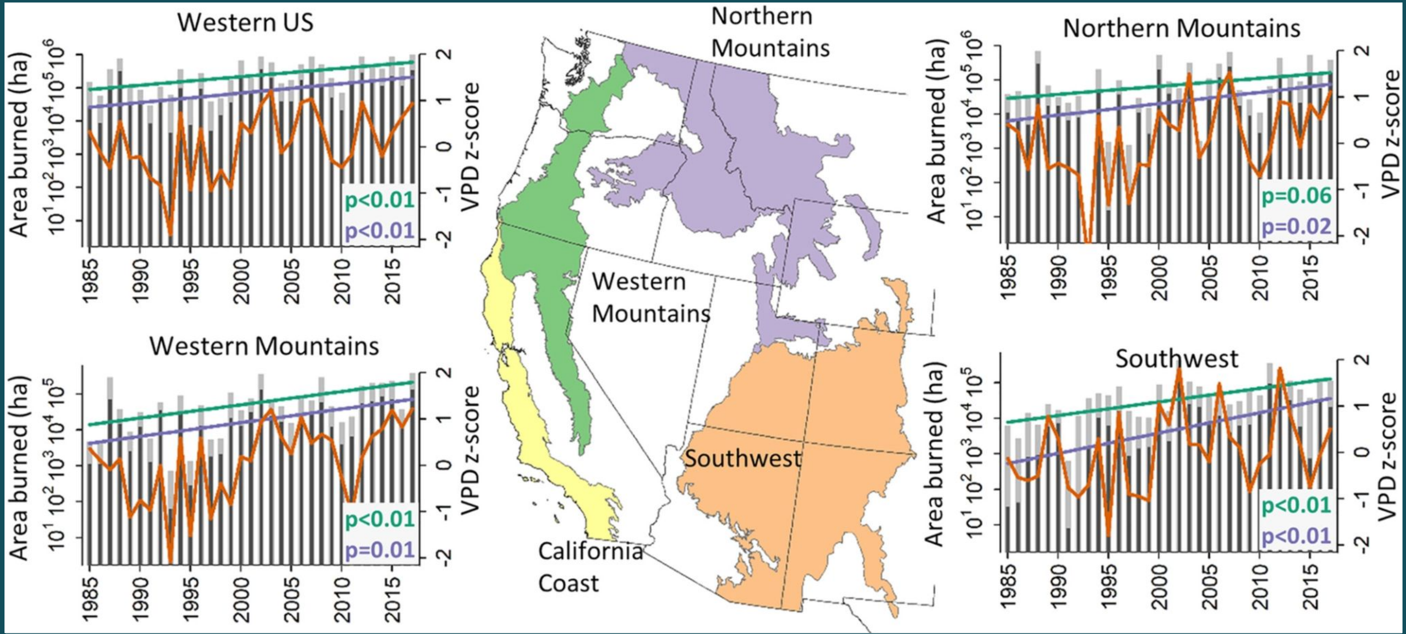
Improving predictions of post-fire forest regeneration by mapping individual surviving trees

Derek Young, Ph.D.
Research Ecologist
UC Davis

UCDAVIS
UNIVERSITY OF CALIFORNIA

Increasing extent of high-severity fire



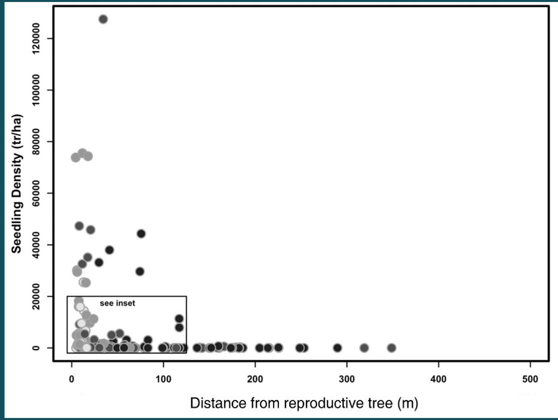
Annual area burned

Annual area burned at high severity

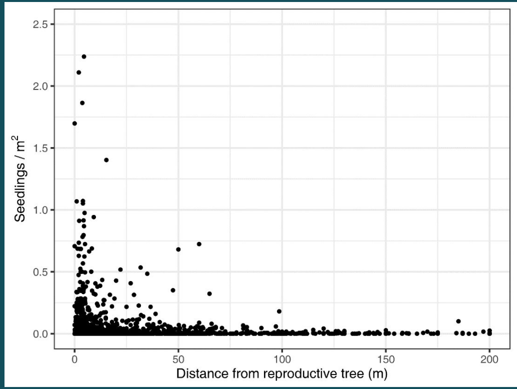
Parks and Abatzoglou 2020


1 cm

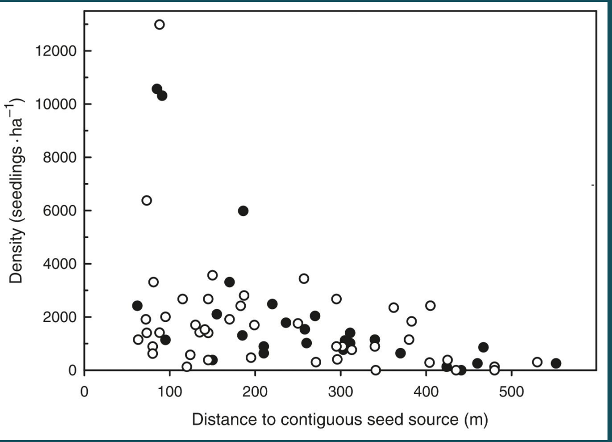
Seedling density vs. distance to surviving trees



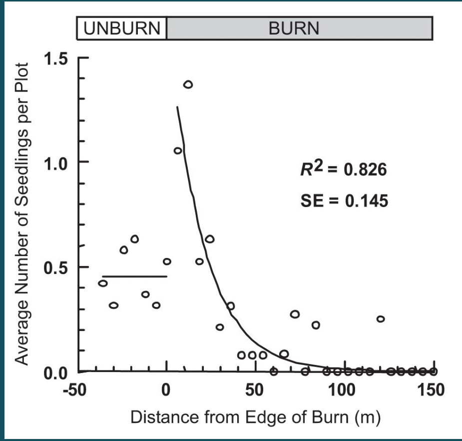
Kemp et al. 2016



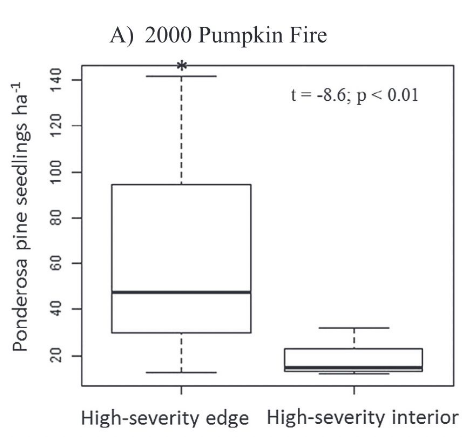
Data from Welch et al. 2017, Young et al. 2019



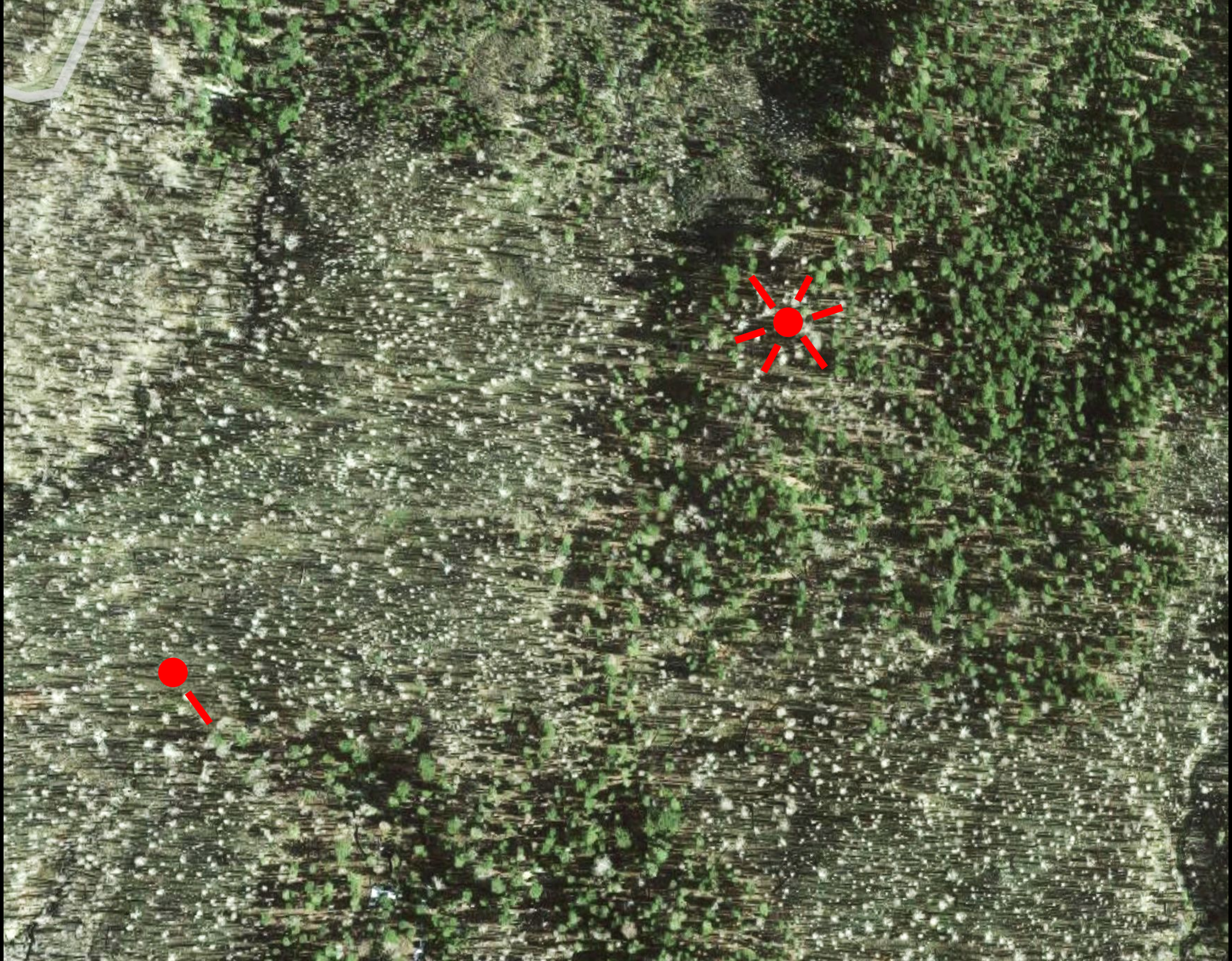
Donato et al. 2009



Bonnet et al. 2005



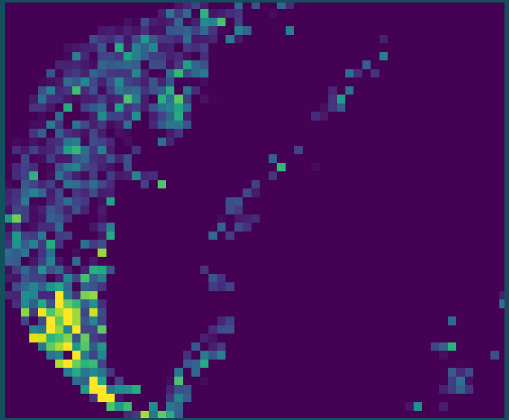
Owen et al. 2017



Incorporating neighborhood seed source density

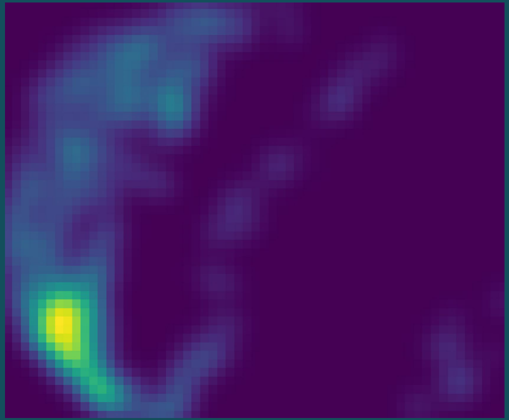
- Live forest cover (%) within a 400-m radius (Tepley et al. 2017)
- Live forest cover (%) and patchiness within 25- to 250-m radii (Peeler & Smithwick 2020)
- Basal area smoothed using a Gaussian kernel (Shive et al. 2018, Stewart et al. 2021)

Live tree basal area



Gaussian smooth

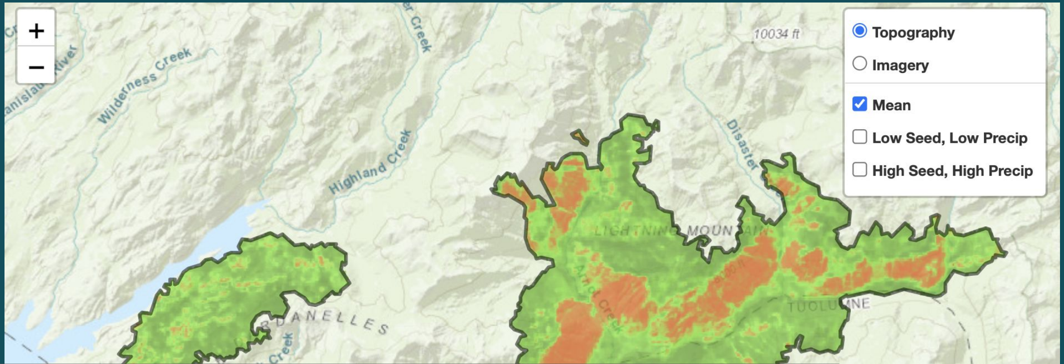
Seed availability proxy

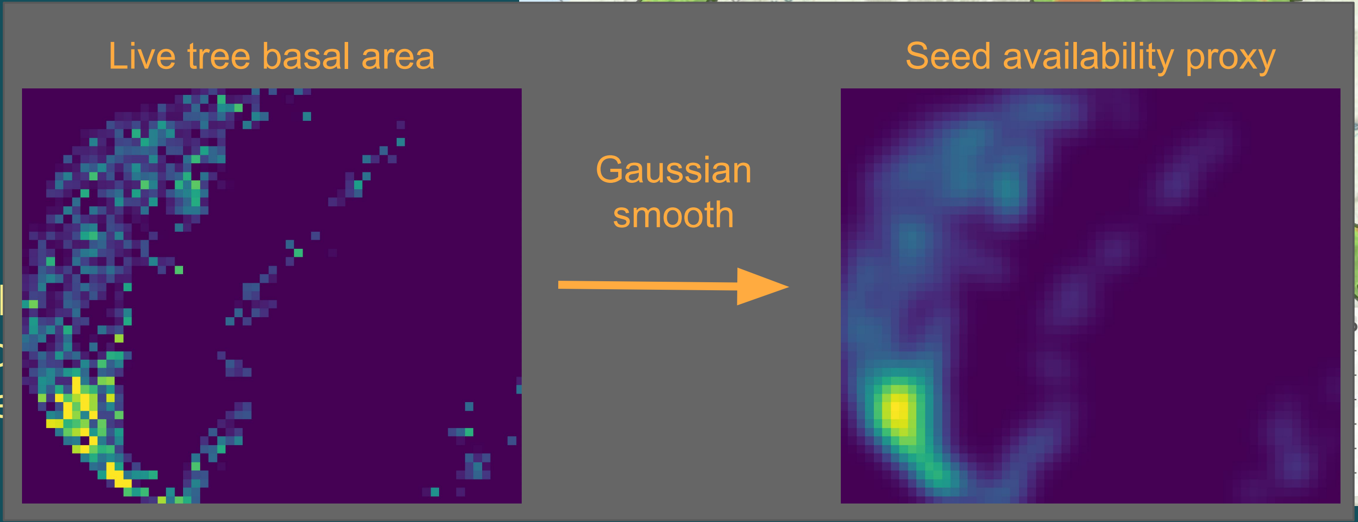


Post-fire conifer regeneration prediction tool

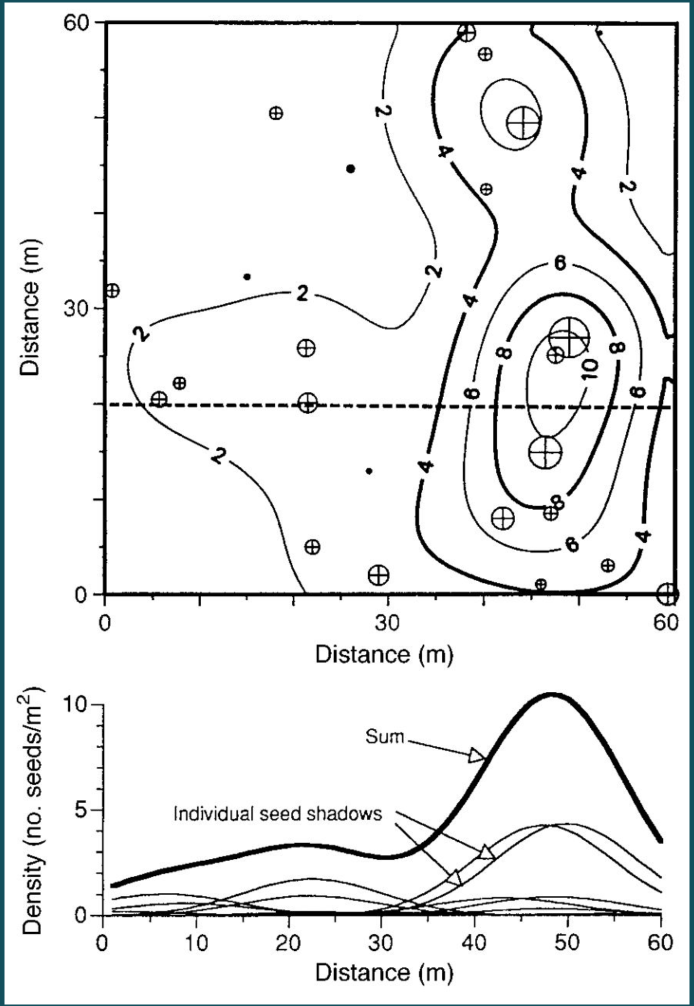
PostCRPT

reforestationtools.org

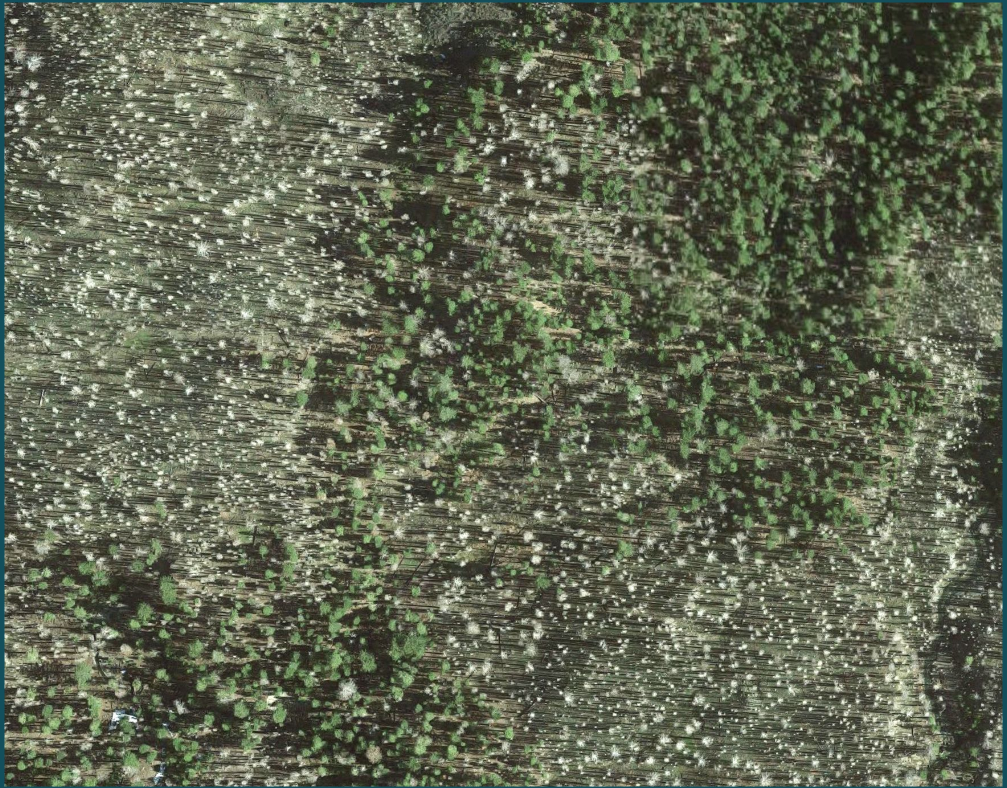




Seed rain is the sum of individual-tree seed shadows

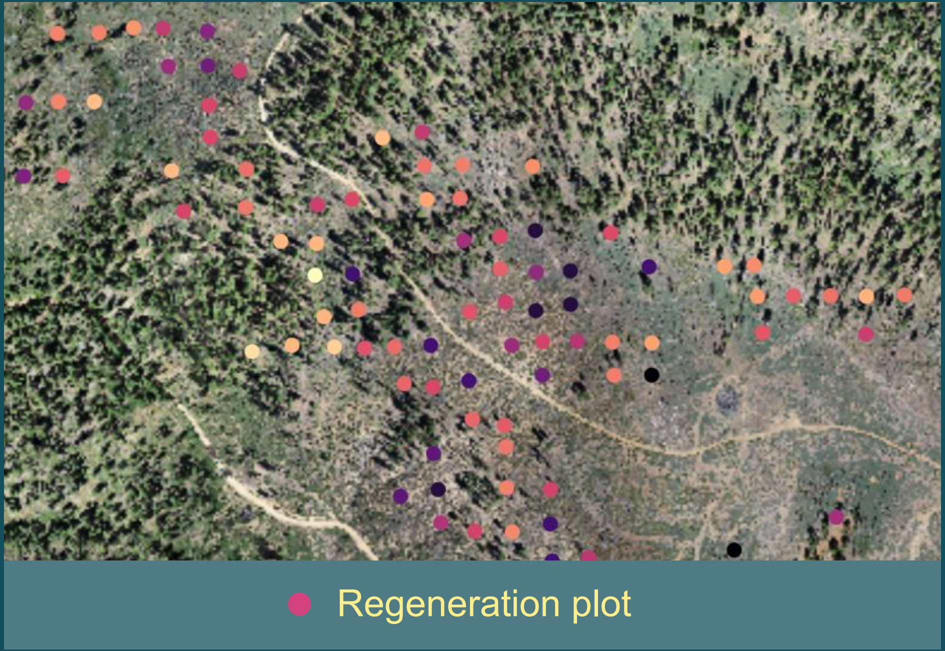


Clark et al. 1999 *Ecology*



Objective

- Predict post-fire seedling density across space based on the locations and sizes of individual surviving trees



Approach

1. Map surviving trees using low-cost drone-based technology
2. Quantify seedling abundance in a dense grid of plots across space
3. Fit a dispersal kernel based on the summed contribution of each tree to each seedling plot

Outline

Drone-based forest mapping

Seed dispersal modeling

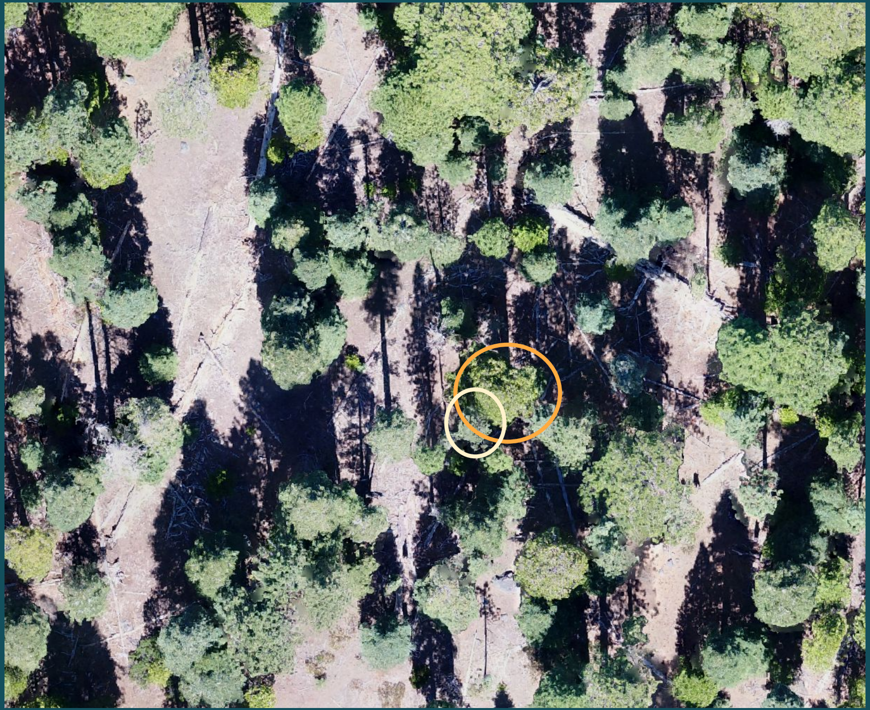
Future of forest mapping

Drone-based forest mapping

USDA NAIP imagery (aerial)

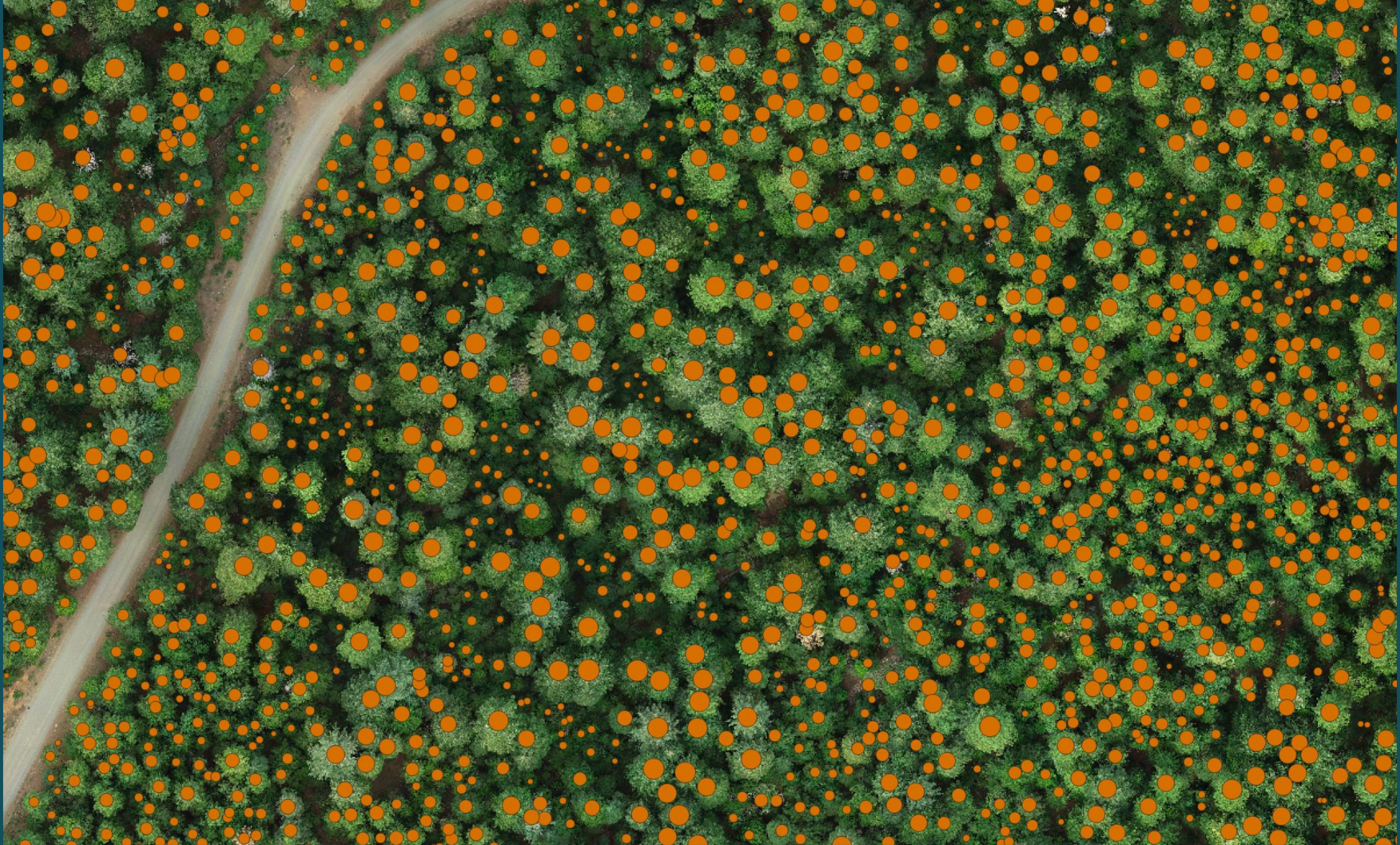
- 60 cm resolution
- Every 2 years
- No 3D structure

Drone imagery



- < 3 cm resolution
- Collect (almost) any time
- 3D structure

Photogrammetry – “Structure from motion”



Parameters to tune (partial list!)

Imagery acquisition

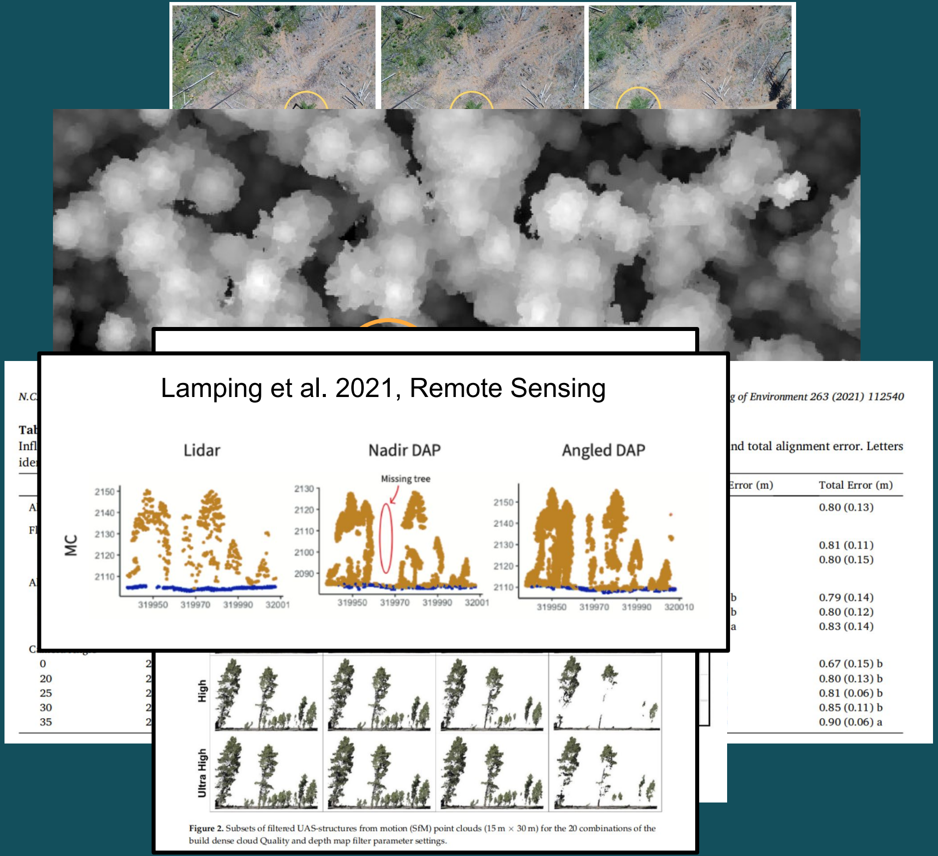
- Flight altitude
- Image overlap
- Camera angle

Photogrammetry

- Processing resolution
- Data filtering

Tree detection

- Canopy height model smoothing
- Local maximum detection algorithm



Parameters tested

Imagery acquisition

- **Flight altitude:** 90 m, 120 m
- **Image overlap:** 80% - 95%
- **Camera angle:** nadir, 25°, composite

Photogrammetry

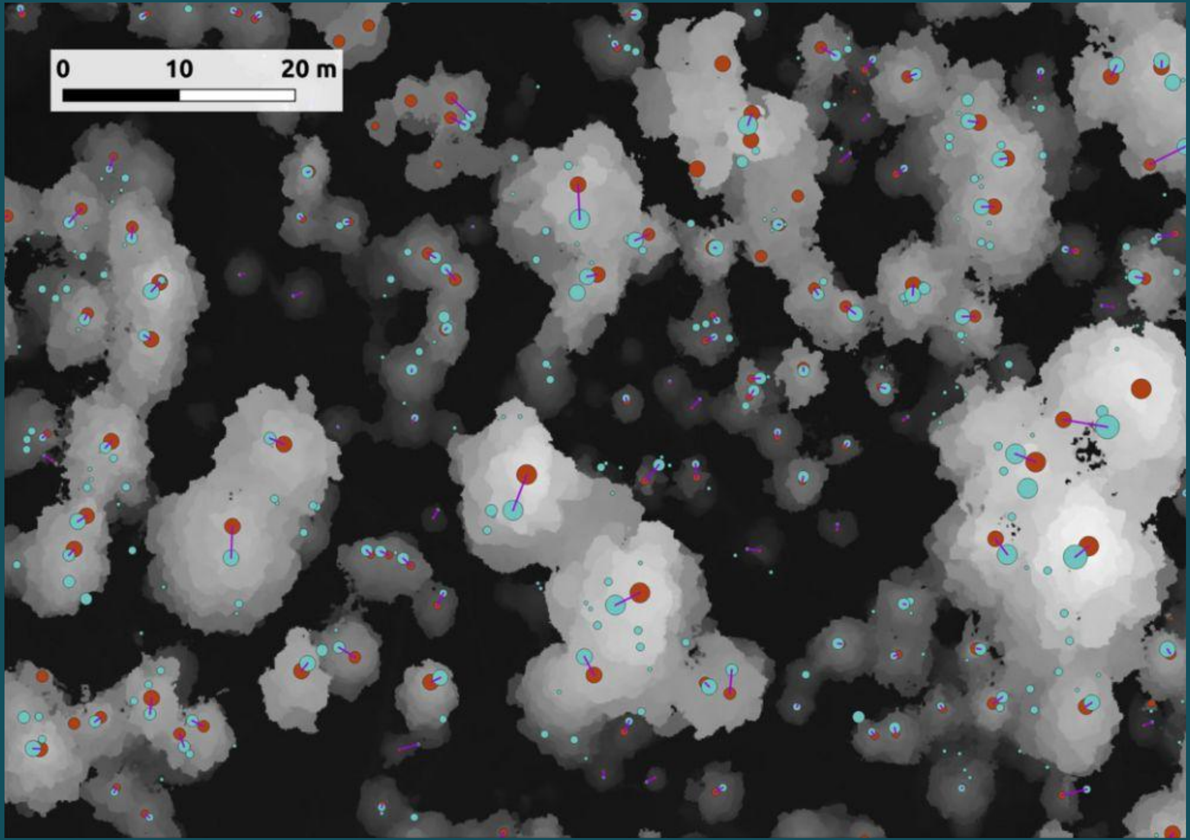
- **Processing resolution:** Orig., downsampled
- **Data filtering:** Mild, moderate, aggressive

Tree detection

- **Canopy height model smoothing:** 0 to 1.5 m focal mean
- **Local maximum detection algorithm:** 228 parameterizations

Young, Koontz, Weeks (2022) *Methods in Ecology and Evolution*

Drone- vs. ground-based maps



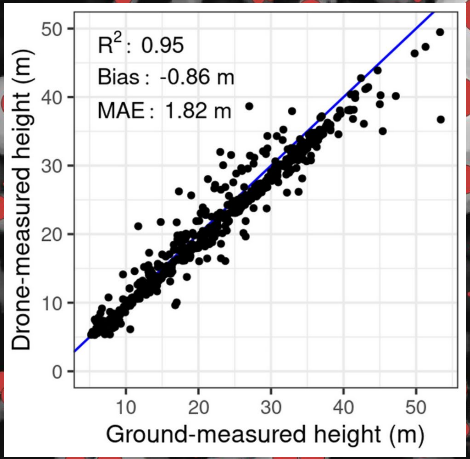
Field-mapped tree

Drone-mapped tree

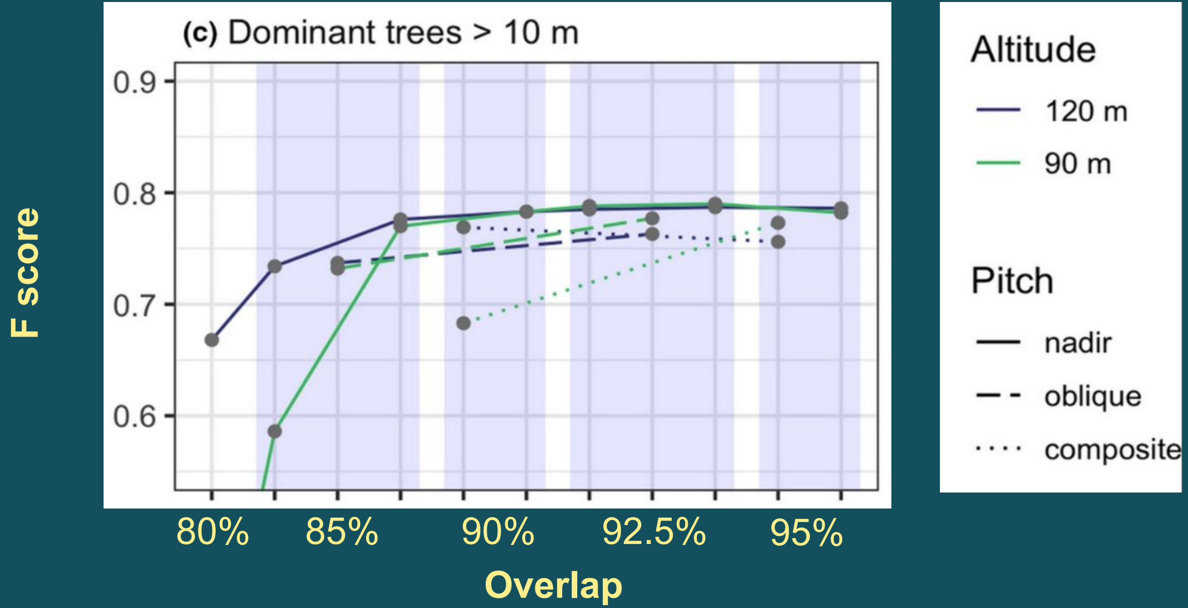
Repeated for every set of parameters (thousands!)

Individual overstory tree detection performance

Tree height	Recall	Precision	F score
> 10 m	0.69	0.90	0.78
> 20 m	0.84	0.89	0.86



Flight altitude and camera pitch



Photogrammetry
Downsampling raw photos

Treetop detection
Variable-radius filter

Young, Koontz, Weeks (2022) *Methods in Ecology and Evolution*

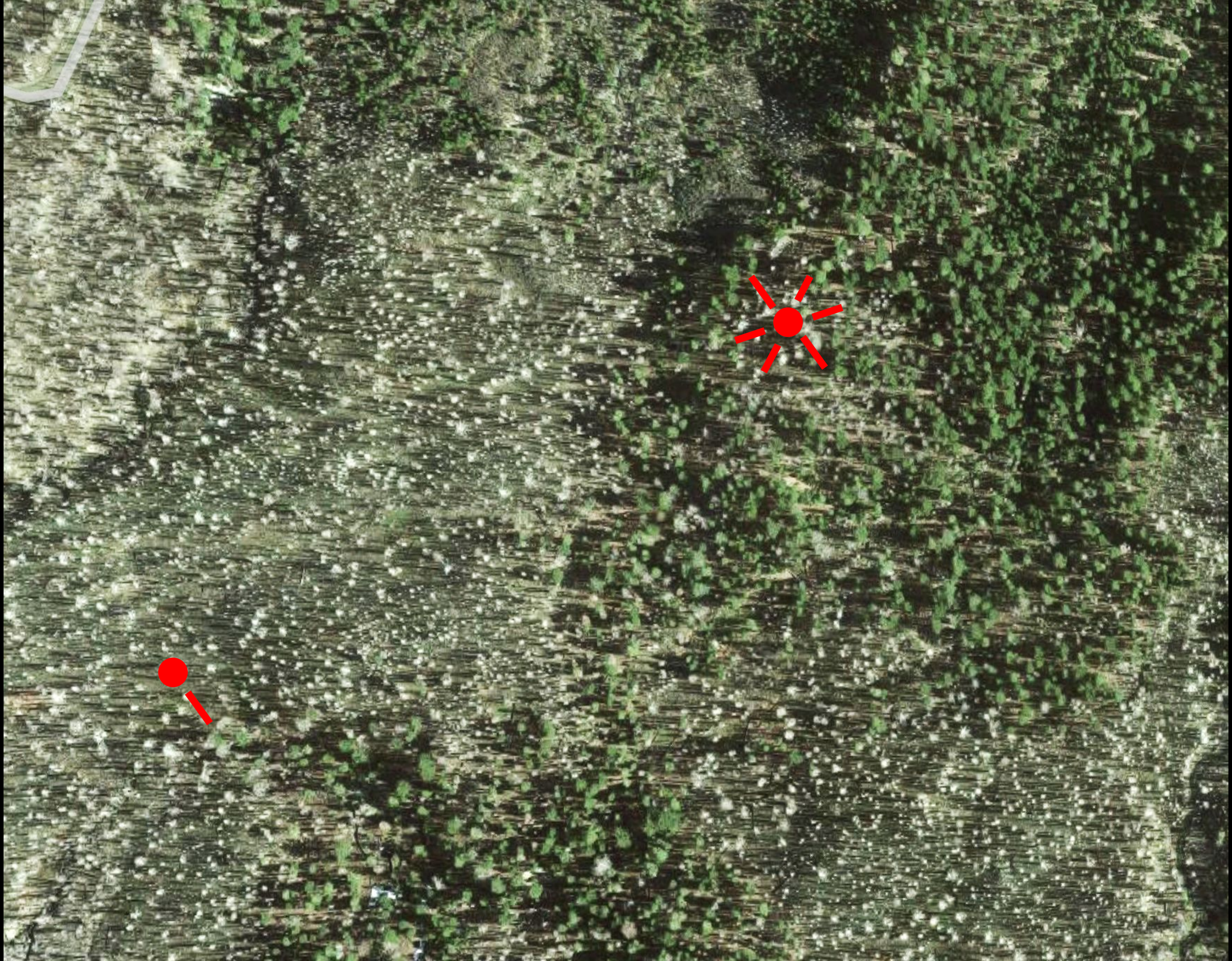
```
calibrateReflectance: # (Metahsape: calibrateReflectance)⋯

alignPhotos: # (Metashape: matchPhotos, alignCameras)
    enabled: True
    downscale: 2 # How much to coarsen the photos when searching for tie points. Higher number for blurrier photos c
    adaptive_fitting: True # Should the camera lens model be fit at the same time as aligning photos?
    keep_keypoints: True # Should keypoints from matching photos be stored in the project? Required if you later war
    reset_alignment: False # When running an alignment, if any of the photos were already aligned, should we keep th
    generic_preselection: True # When matching photos, use a much-coarsened version of each photo to narrow down the
    reference_preselection: True # When matching photos, use the camera location data to narrow down the potential r
    reference_preselection_mode: Metashape.ReferencePreselectionSource # When matching photos, use the camera locati

filterPointsUSGS:⋯

optimizeCameras: # (Metashape: optimizeCameras)
    enabled: True
    adaptive_fitting: True # Should the camera lens model be fit at the same time as optimizing photos?

buildPointCloud: # (Metashape: buildDepthMaps, buildPointCloud, (optionally) classifyGroundPoints, and exportPoints)
    enabled: True
    ## For depth maps (buildDepthMaps)
    downscale: 2 # How much to coarsen the photos when searching for matches to build the point cloud. For large pho
    filter_mode: Metashape.ModerateFiltering # How to filter the point cloud. Options are NoFiltering, MildFiltering
    reuse_depth: False # Purpose unknown.
    ## For point cloud (buildPointCloud)
    keep_depth: False # Purpose unknown.
    ## For both
    max_neighbors: 100 # Maximum number of neighboring photos to use for estimating point cloud. Higher numbers may
    ## For ground point classification (classifyGroundPoints). Definitions here: https://www.agisoft.com/forum/index
    classify_ground_points: True # Should ground points be classified as a part of this step? Must be enabled (eithe
    ## For point cloud export (exportPoints)
    export: True # Whether to export point cloud file.
    classes: "ALL" # Point classes to export. Must be a list. Or can set to "ALL" to use all points. An example of a

classifyGroundPoints: # (Metashape: classifyGroundPoints) # classify points, IF SPECIFIED as a component of buildPoi
    max_angle: 15.0
    max_distance: 1.0
```

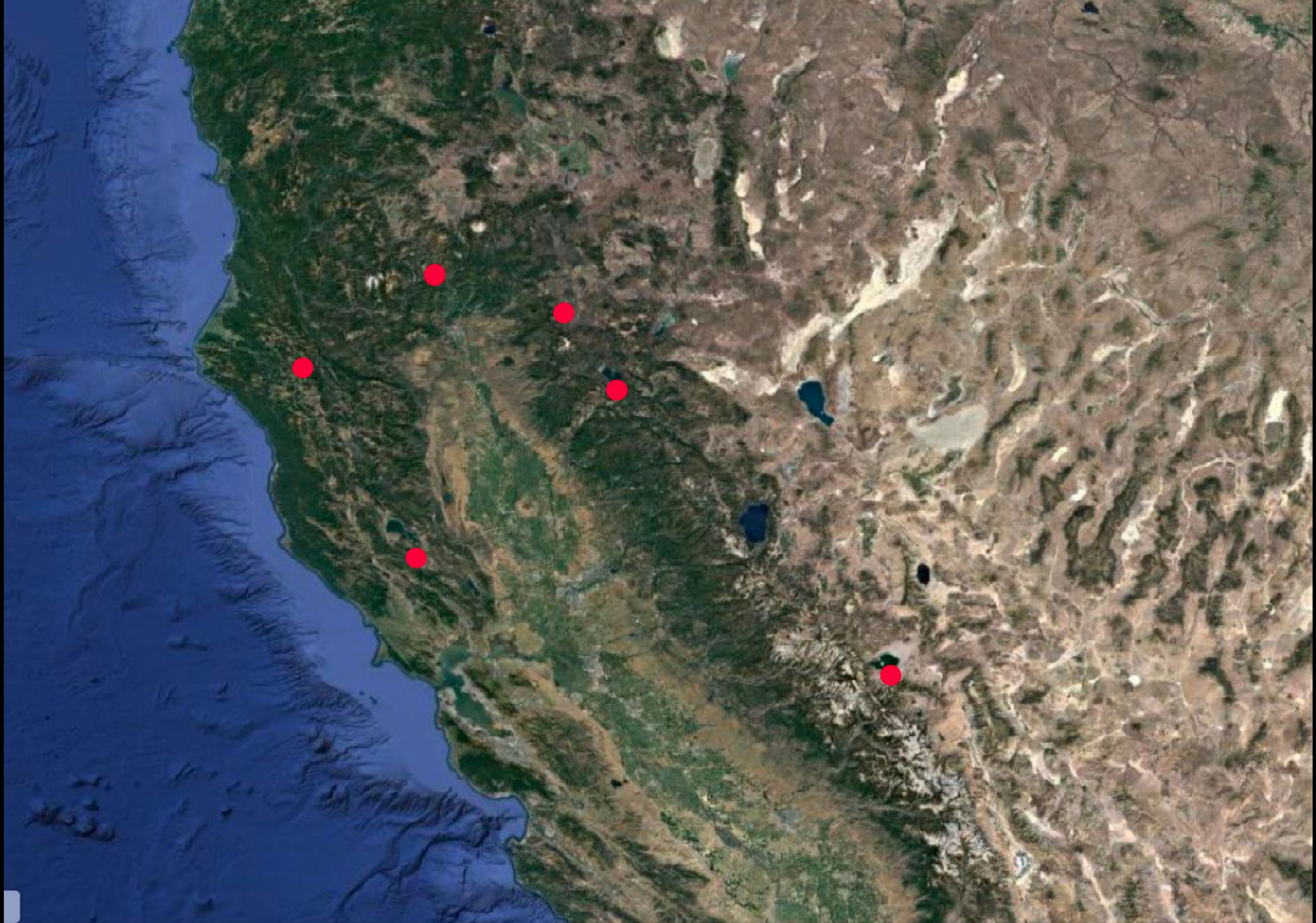
Edit Pins Watch 0 Fork 25 Star 9

https://github.com/open-forest-observatory/automate-metashape

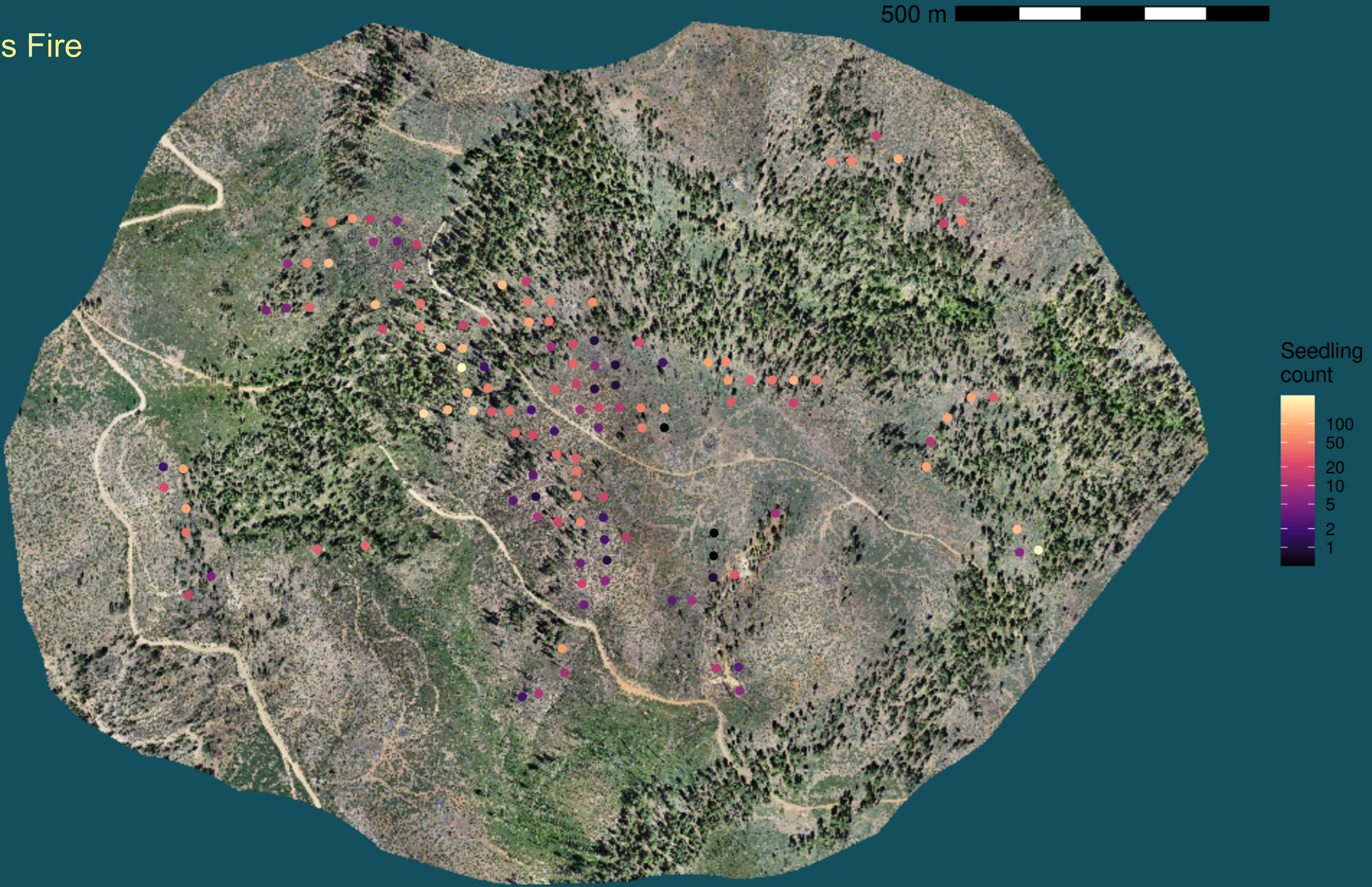
Seed dispersal modeling

for predicting post-fire regeneration

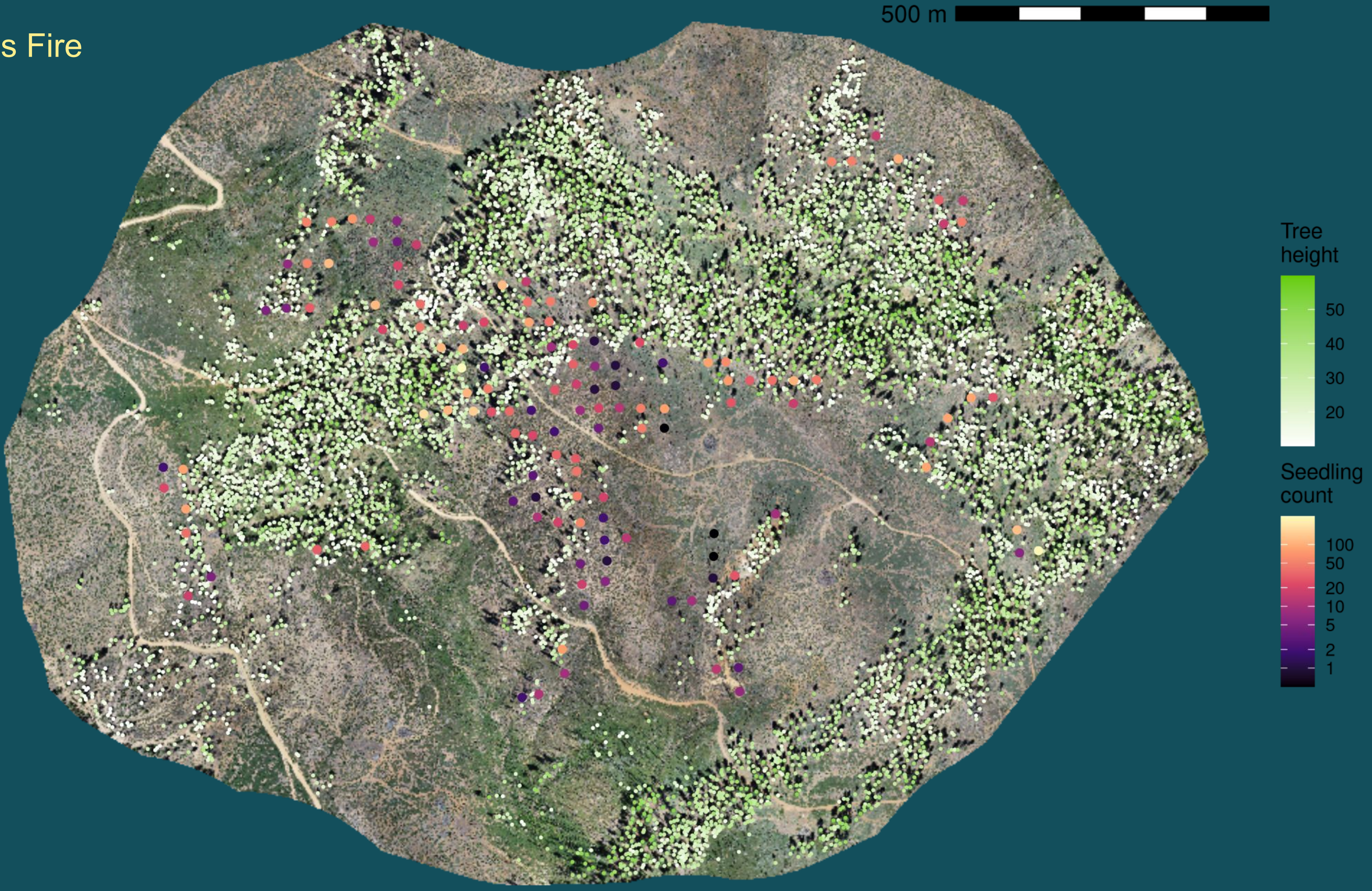




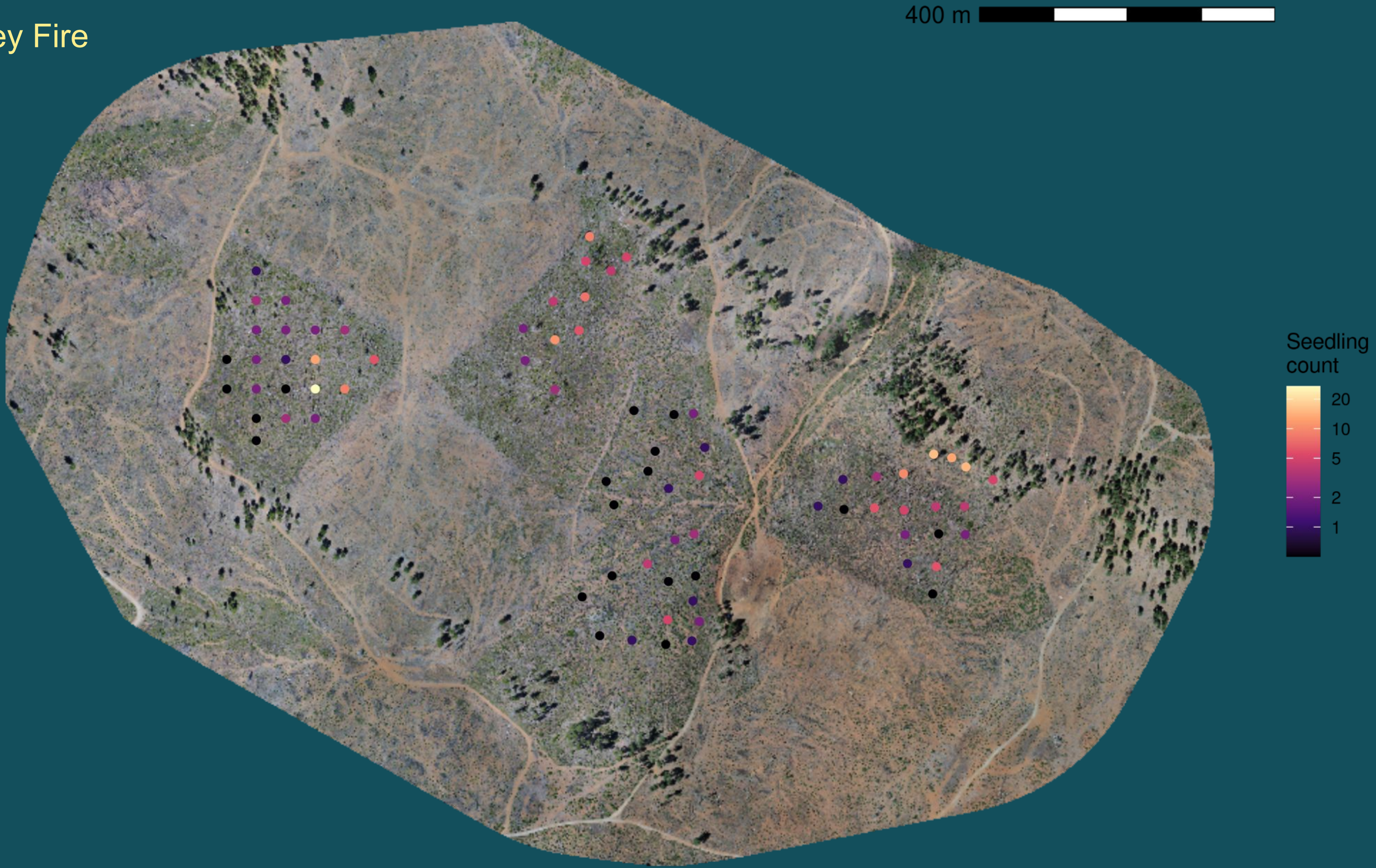
2012 Chips Fire



2012 Chips Fire

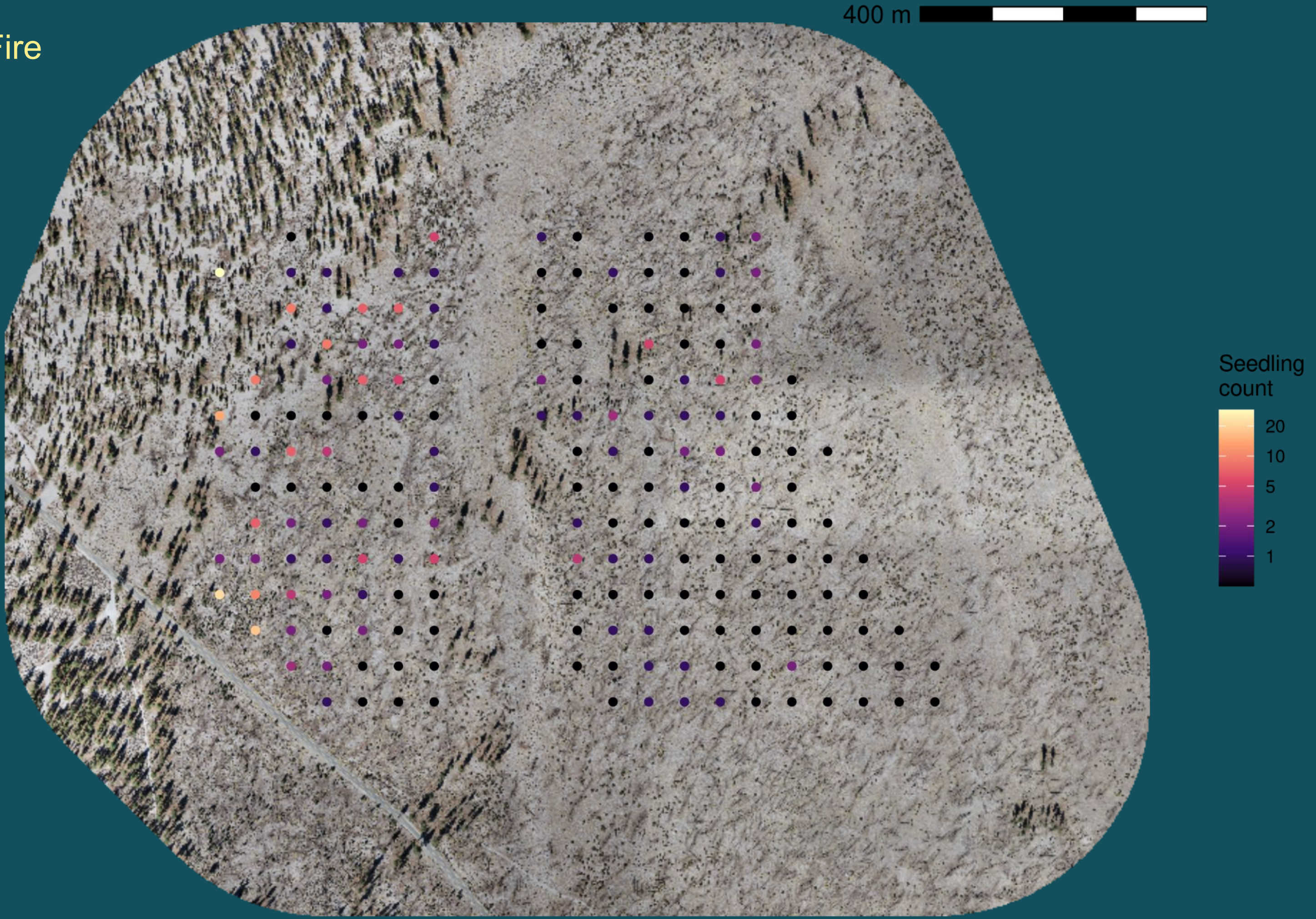


2015 Valley Fire

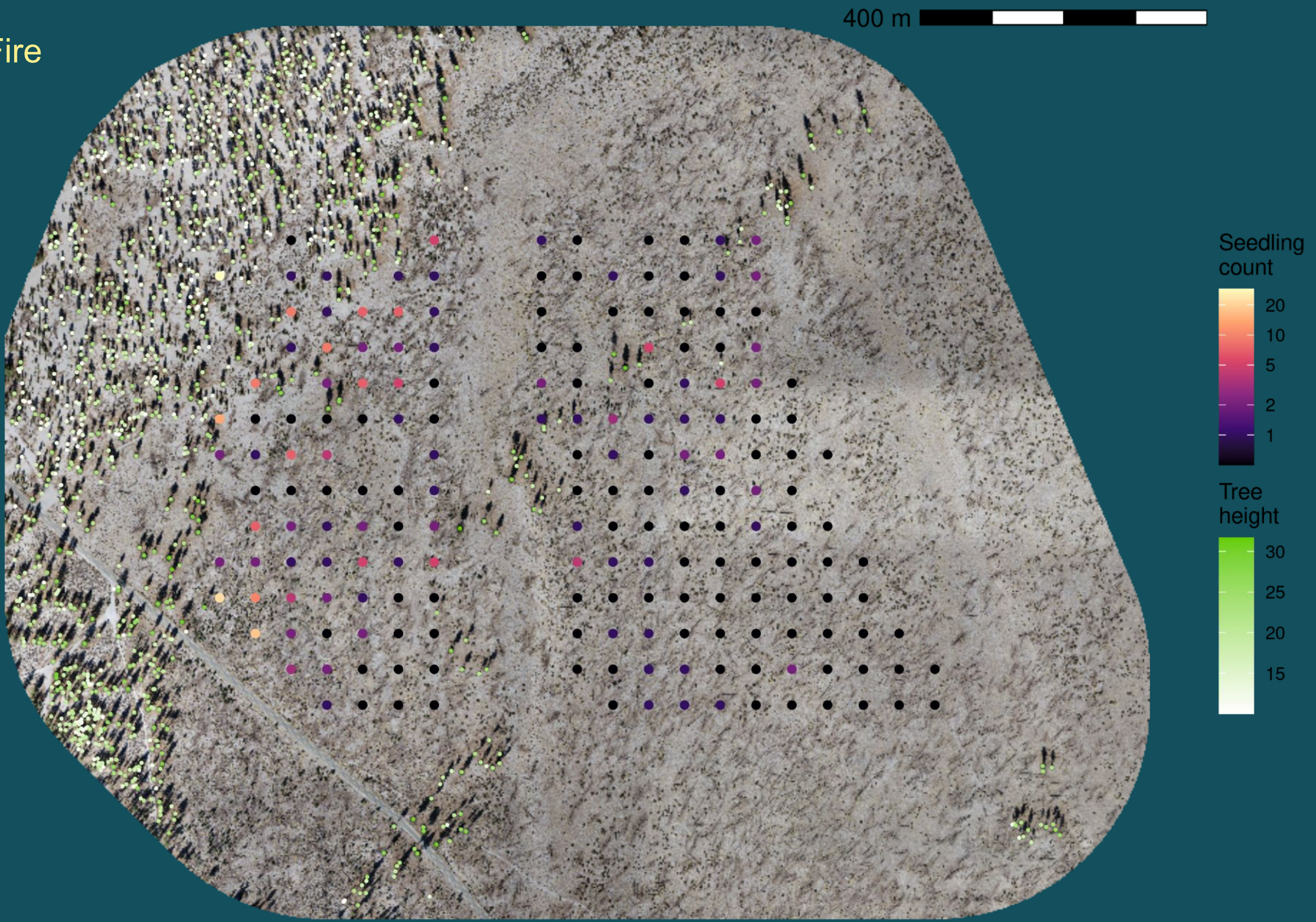


2015 Valley Fire
400 m
Seedling count
20
10
5
2
1
Tree height
40
30
20

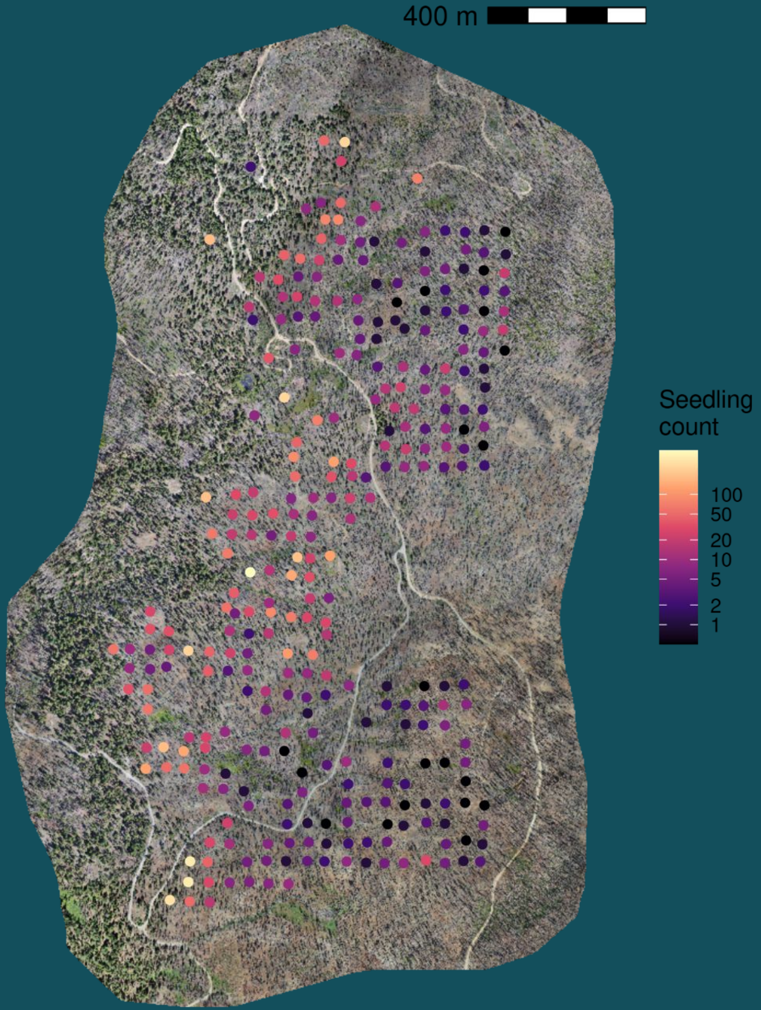
2001 Crater Fire



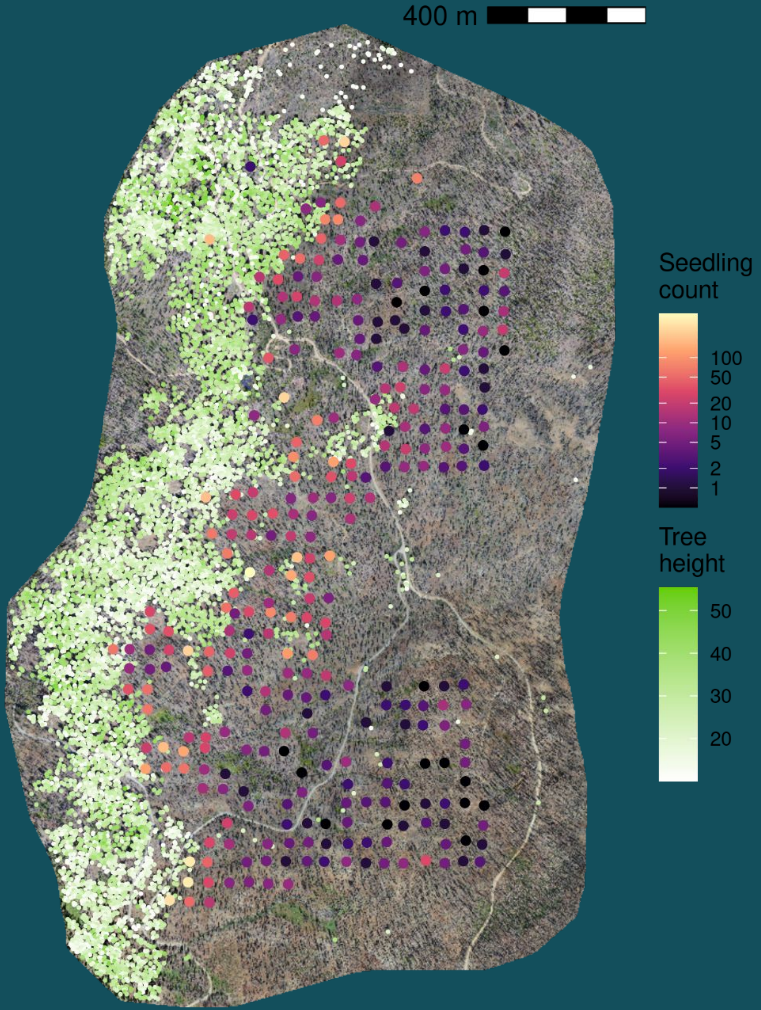
2001 Crater Fire



2018 Delta Fire



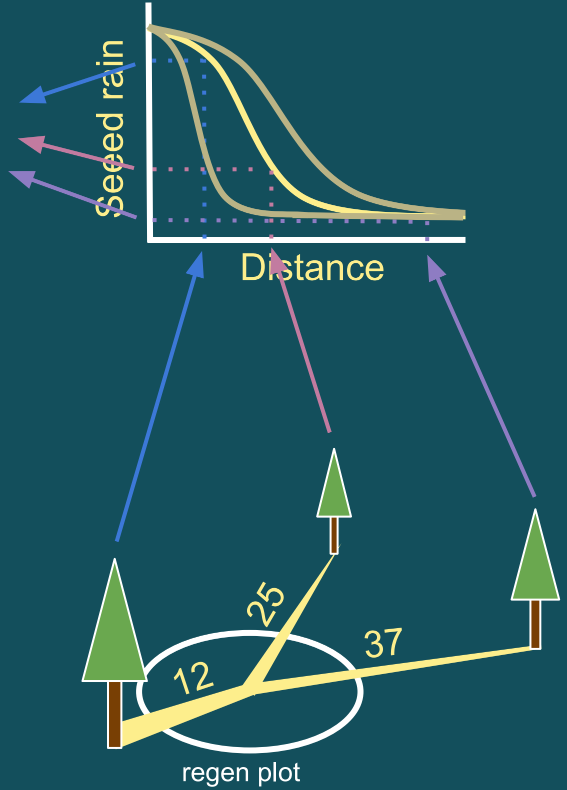
2018 Delta Fire



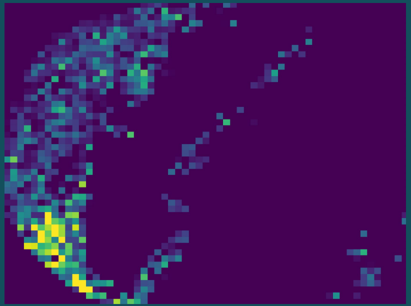
300 **hectares**
30,000 **drone photos**
8,305 **trees**
305 **regen plots**

Traditional model: $\text{seeds in plot} = \alpha + \square \cdot \text{smoothed seed input}$

Kernel model: $\text{seeds in plot} = \sum_{\text{trees}} (\text{seed input})$

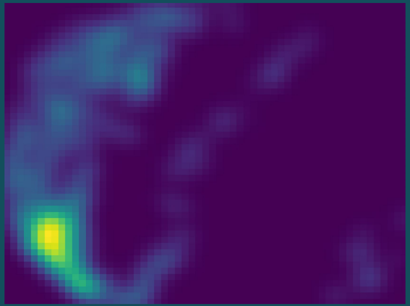


Live tree basal area



Gaussian smooth

Seed availability proxy



Seedling density at a plot:

$$\underbrace{\hat{S}_j}_{\text{Seedling density at plot } j} = \sum_i \underbrace{\beta b_i}_{\text{Fecundity of tree } i} \underbrace{F(r_{ij})}_{\text{Dispersal kernel val for plot-tree distance}}$$

b_i = tree diameter
r_{ij} = plot-tree dist.

Exponential power kernel:

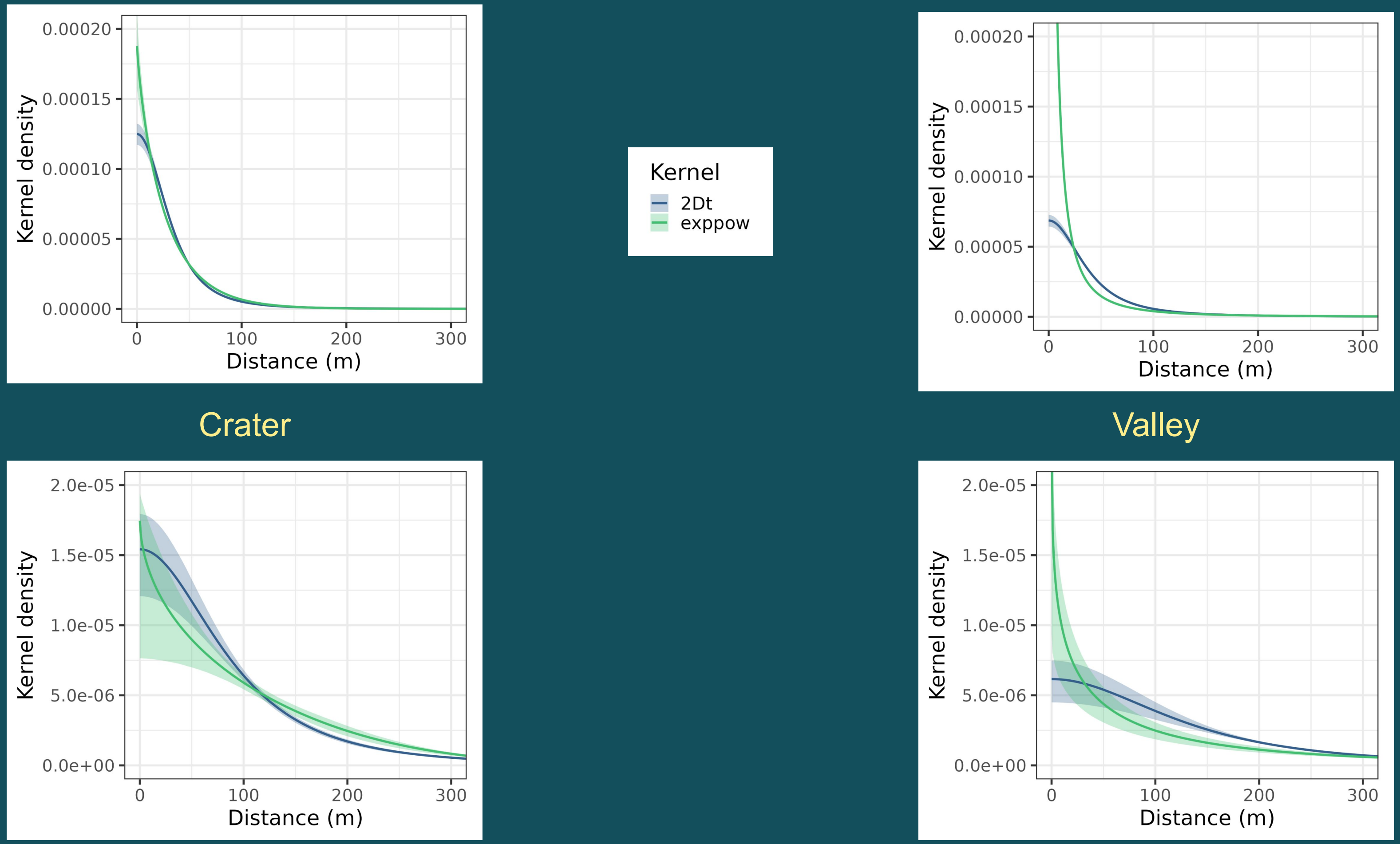
$$F(r) = \frac{k}{2\pi a^2 \Gamma(\frac{2}{k})} e^{\left[-\left(\frac{r}{a}\right)^k\right]}$$

Methods and code (R and Stan) for Bayesian parameter estimation: **Marchand et al. (2019)** ***Ecology***

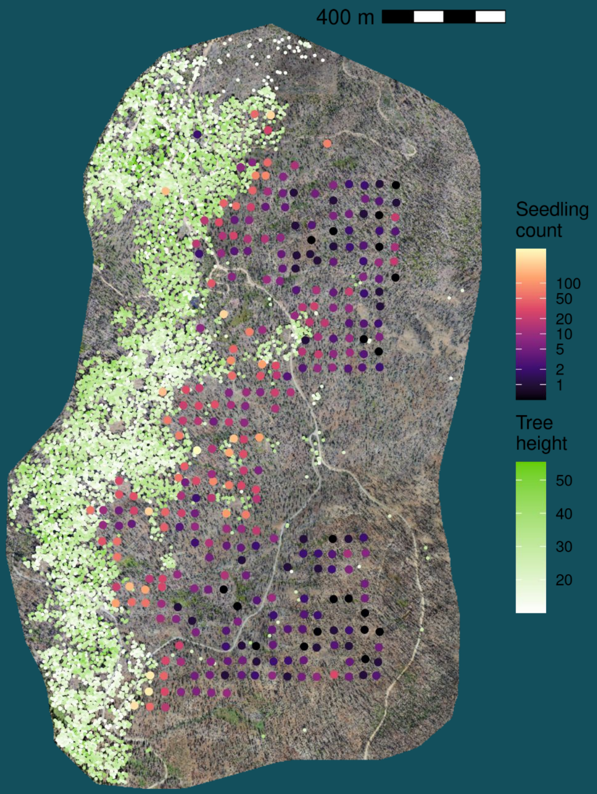
Fitted dispersal kernels

Chips

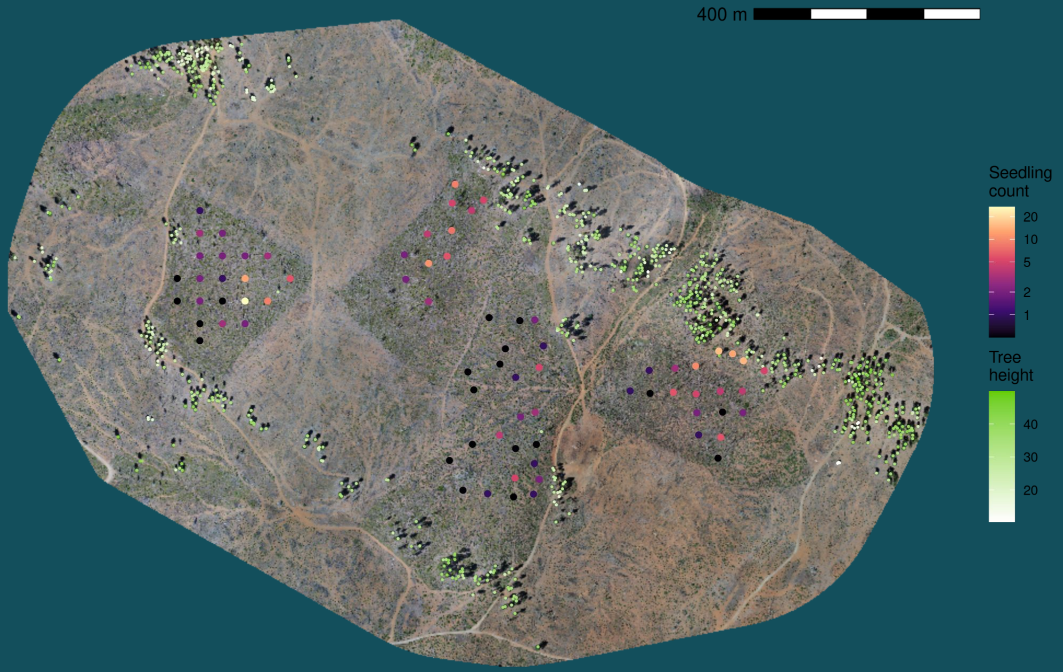
Delta



2018 Delta Fire

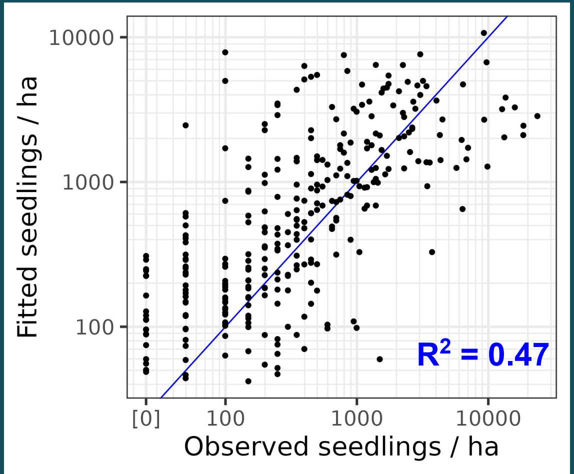


2015 Valley Fire

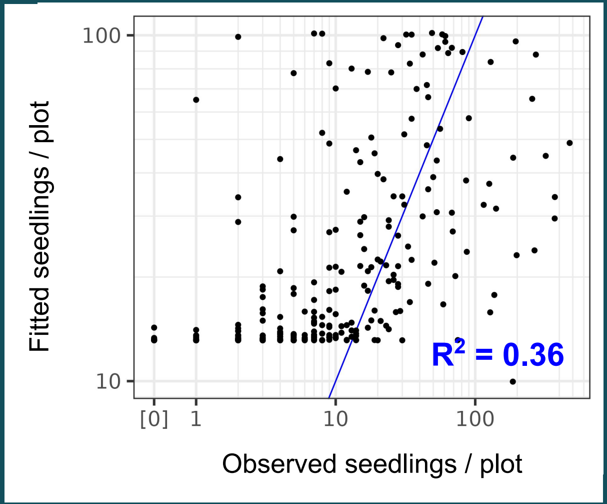


2018 Delta Fire

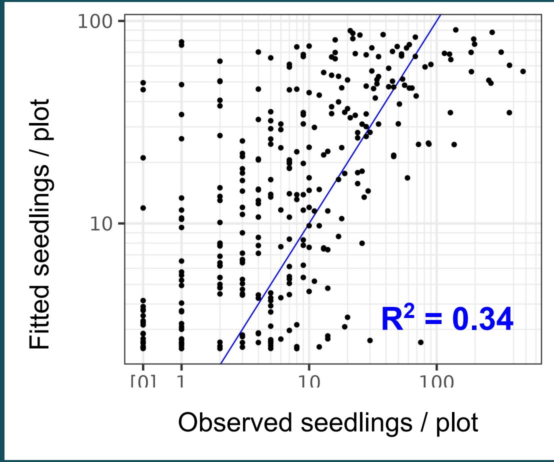
Fitted kernel (2Dt)



Gaussian smooth

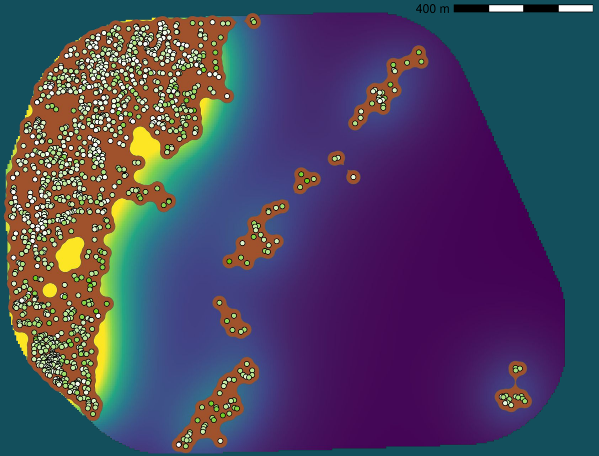


Distance to nearest

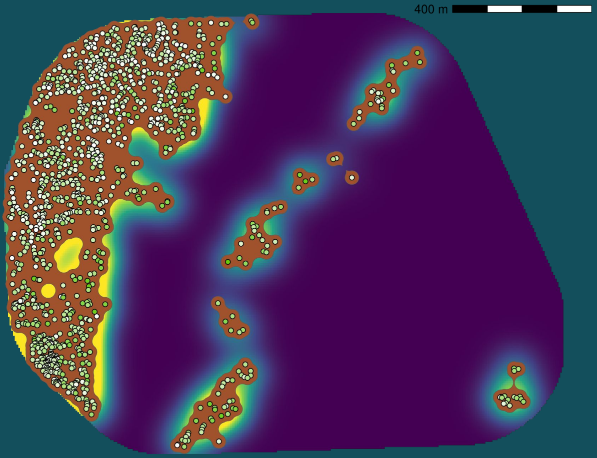


2001 Crater Fire

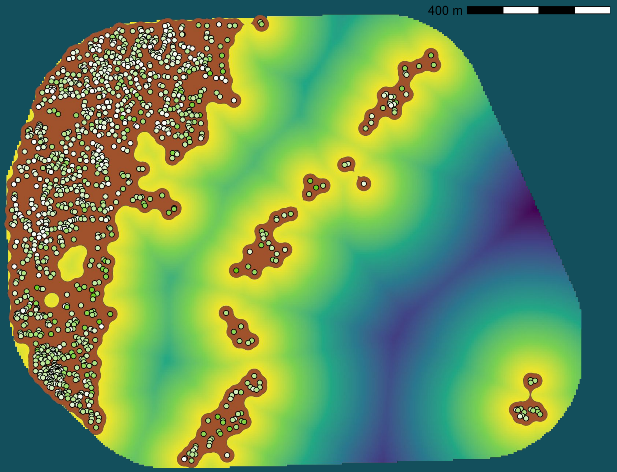
Fitted kernel (2Dt)



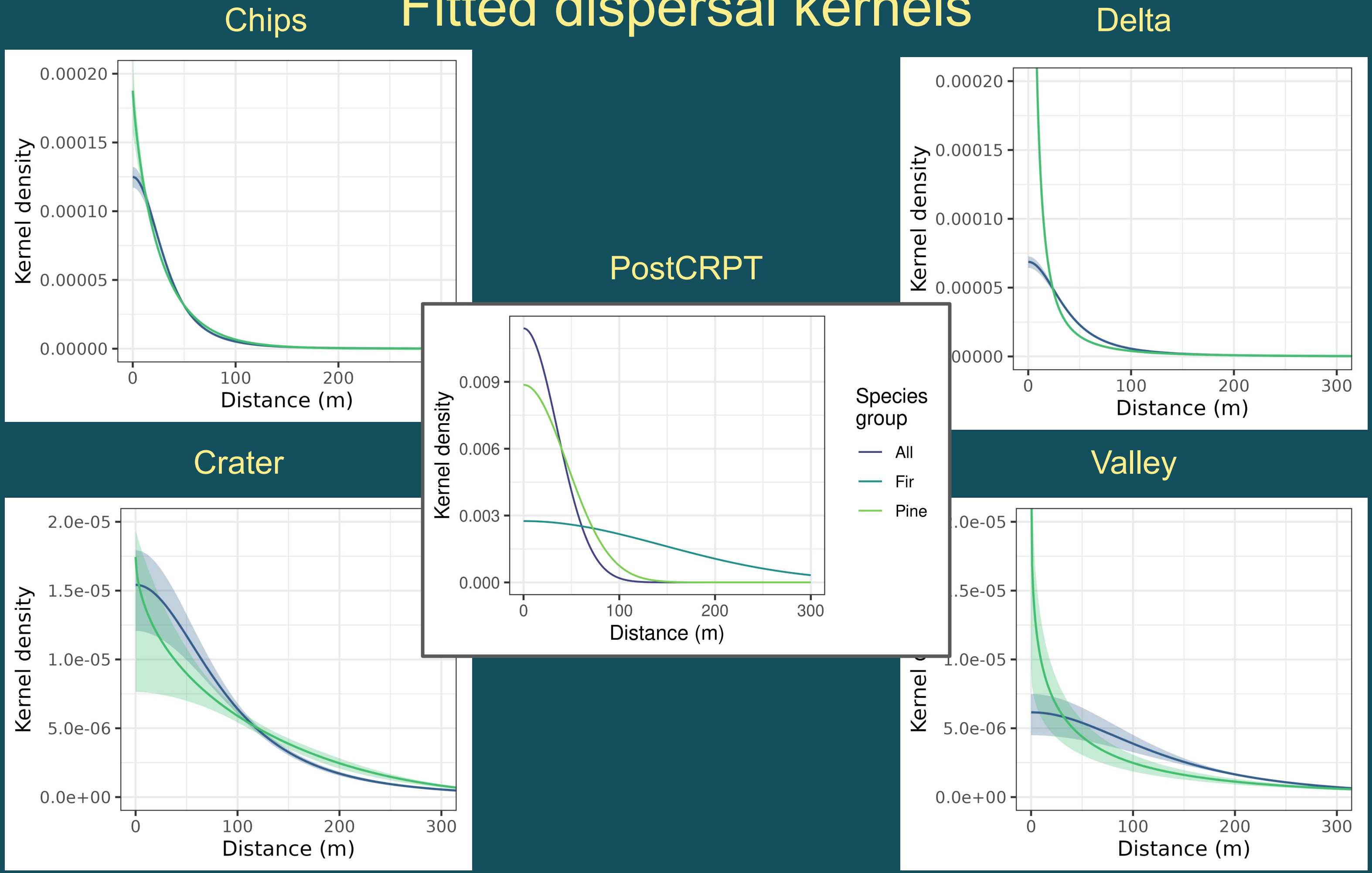
Gaussian smooth



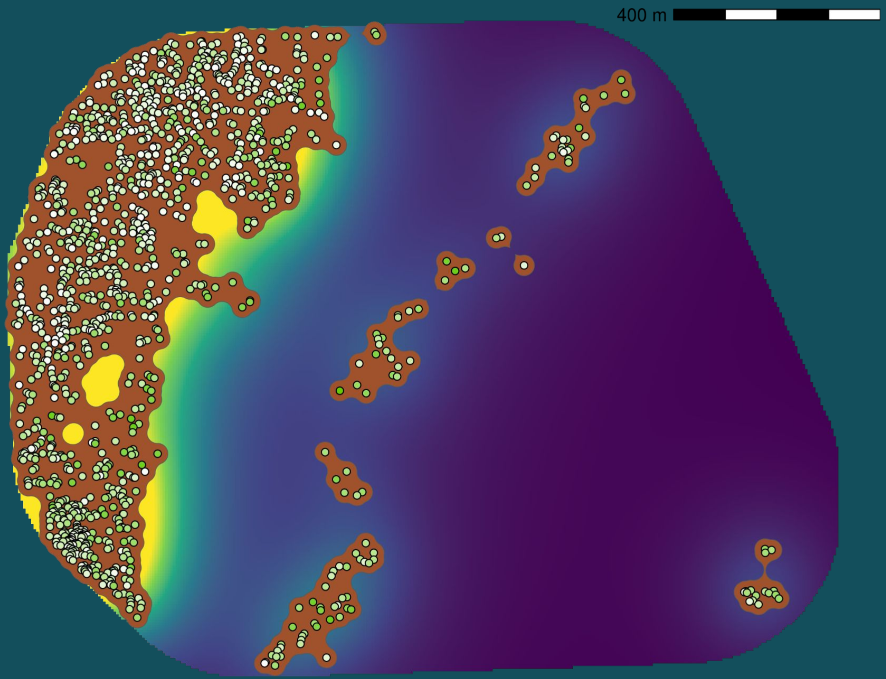
Distance to nearest



Fitted dispersal kernels

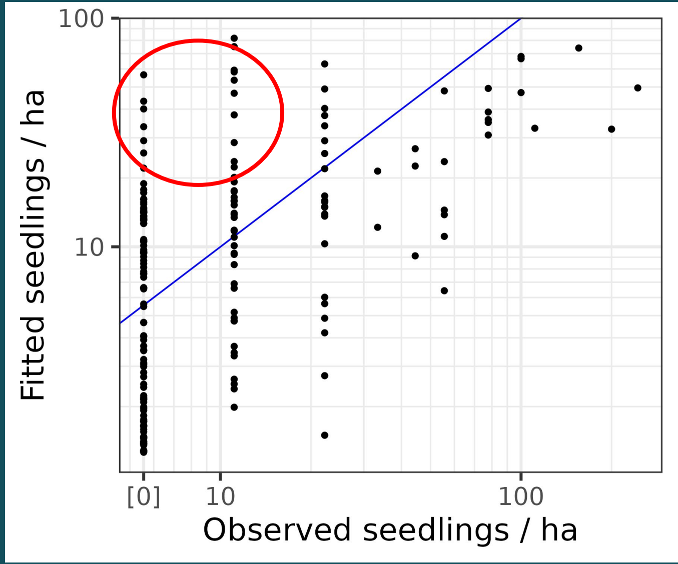


Individual tree-based regeneration prediction tool
(forthcoming)



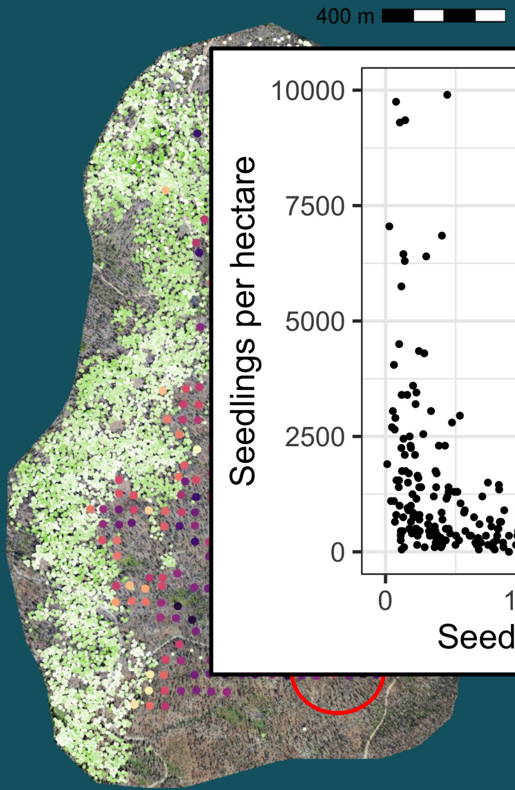
reforestationtools.org

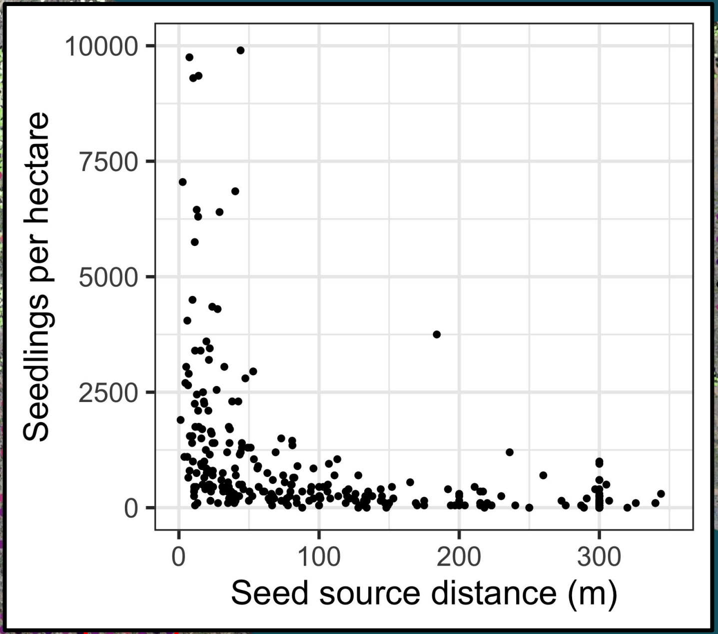
Explaining outliers: Weak regeneration



Explaining outliers: Strong regeneration

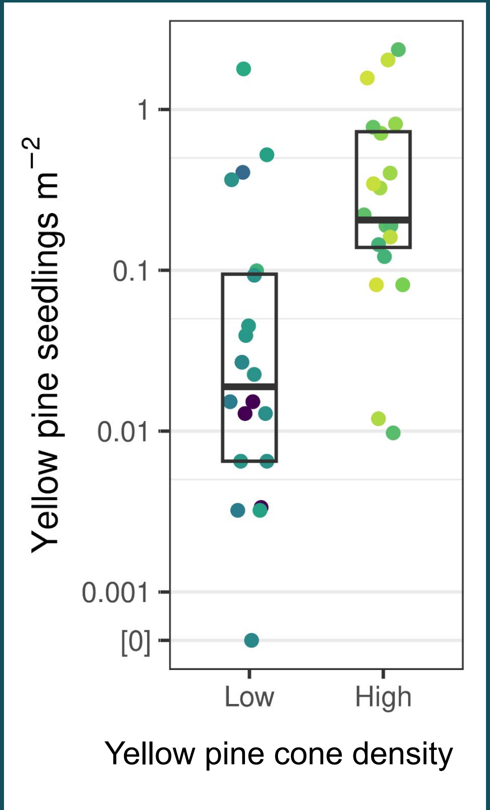
2018 Delta Fire





2015 Valley Fire

Explaining outliers: Strong regeneration



Potential explanations

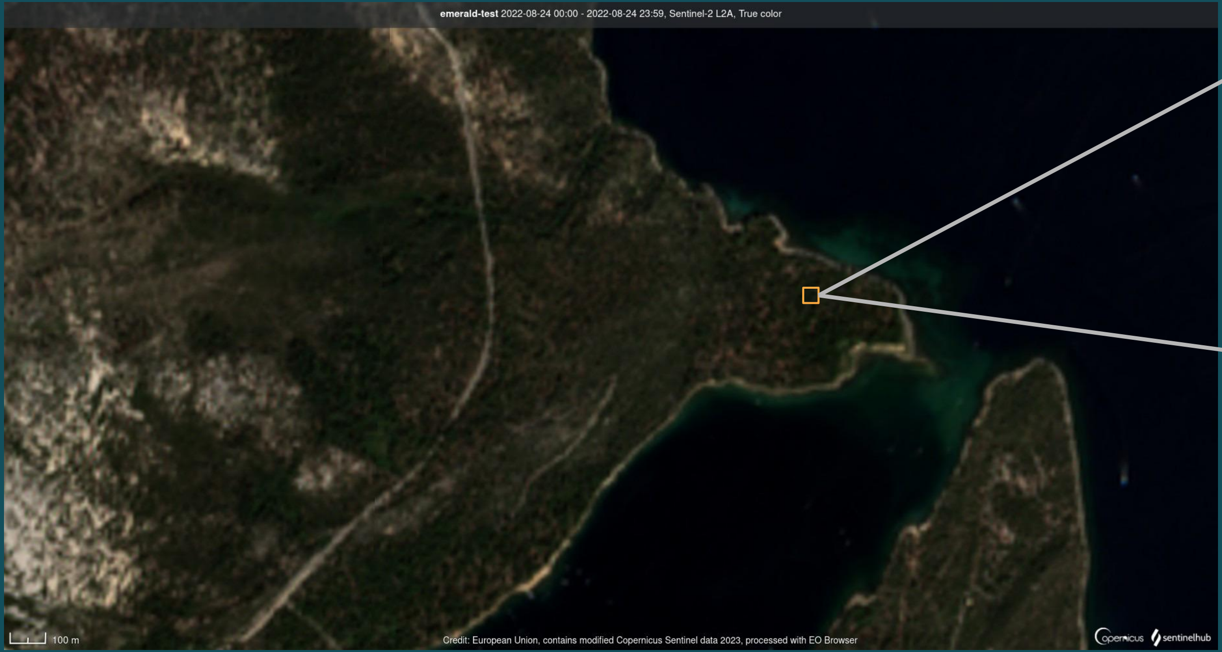
- Delayed mortality
- Aerial seed banking

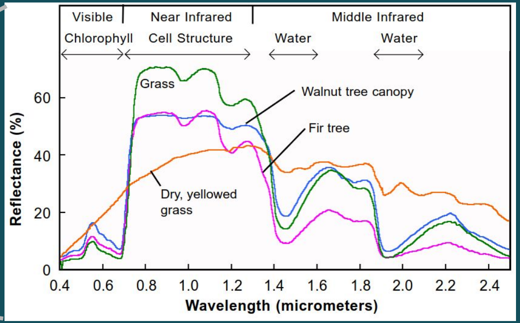
Young et al. *in prep.*

Next steps in drone-based forest mapping

Species ID

"Traditional" multispectral ID





Species ID

Computer vision on drone imagery

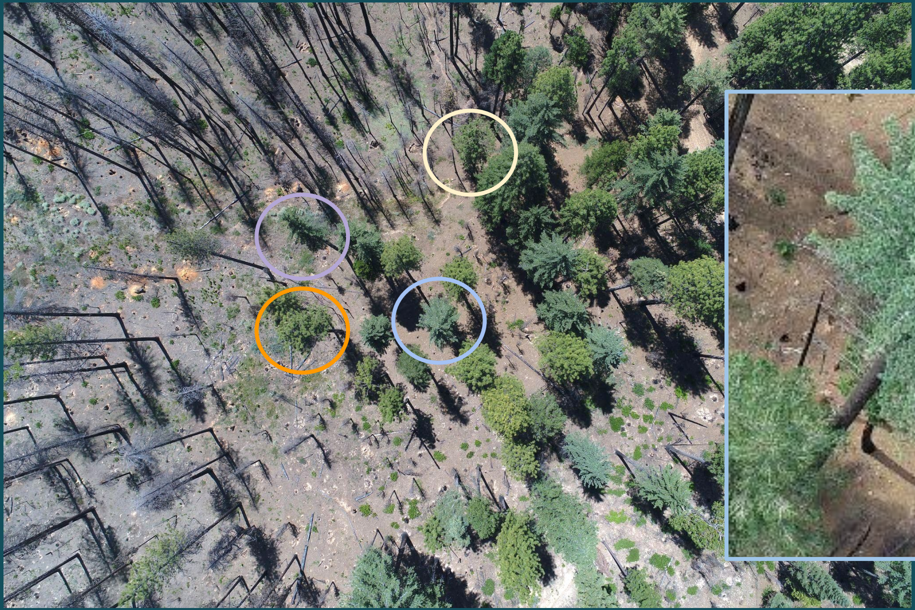
pitbull

ponderosa pine

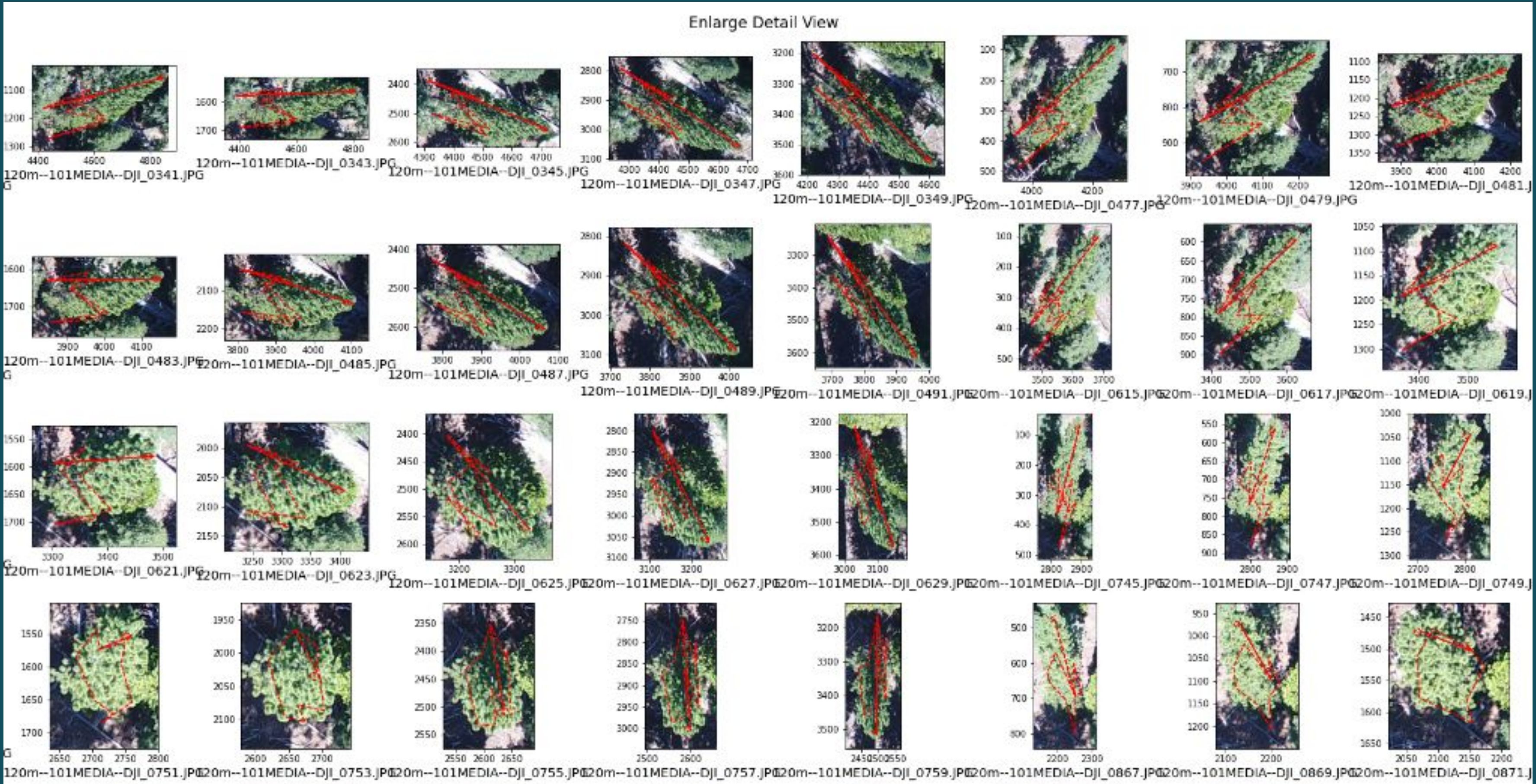
Species ID

Computer vision (AI) for taxonomic ID

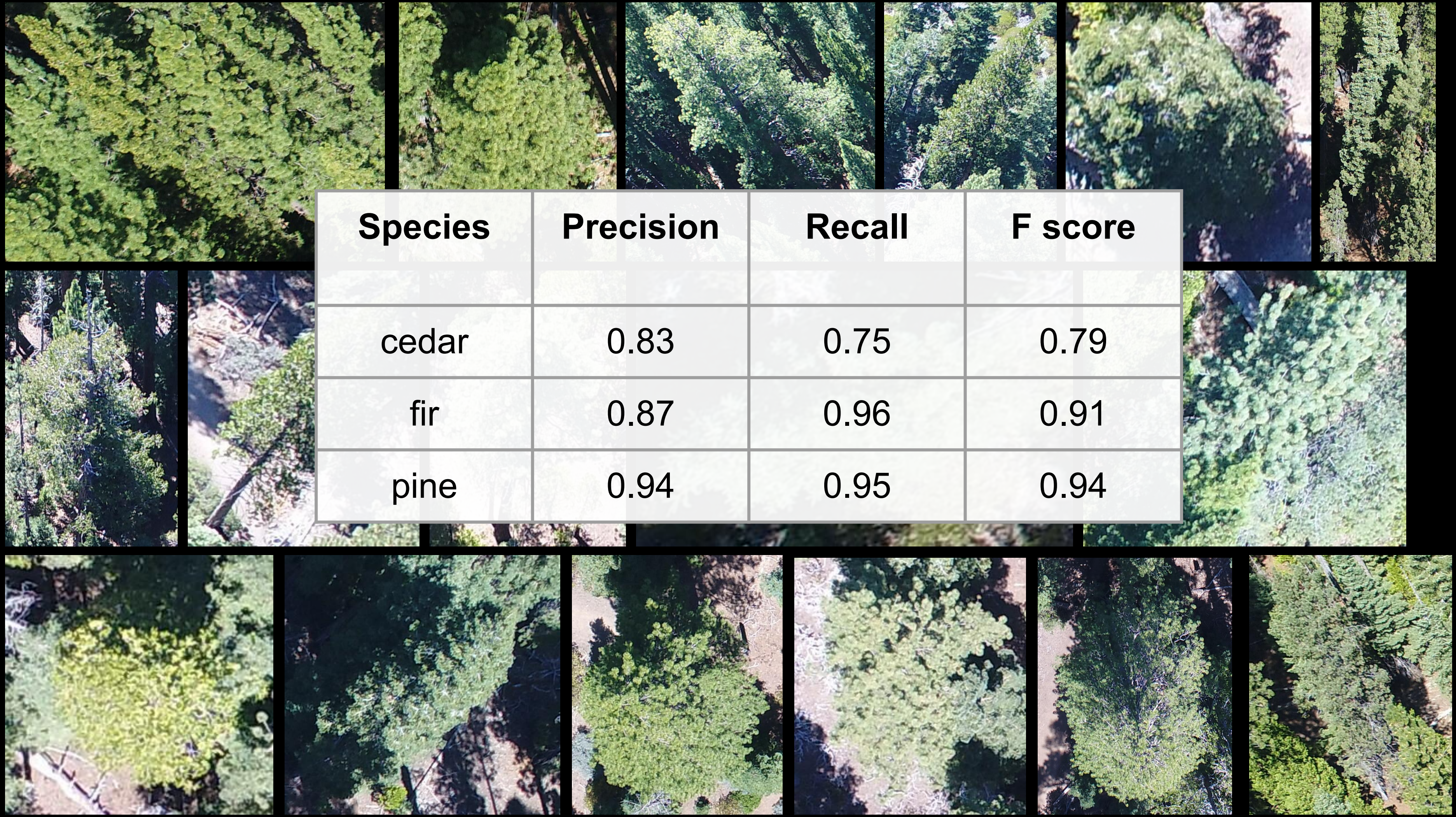
120 m altitude, nadir (0°) camera



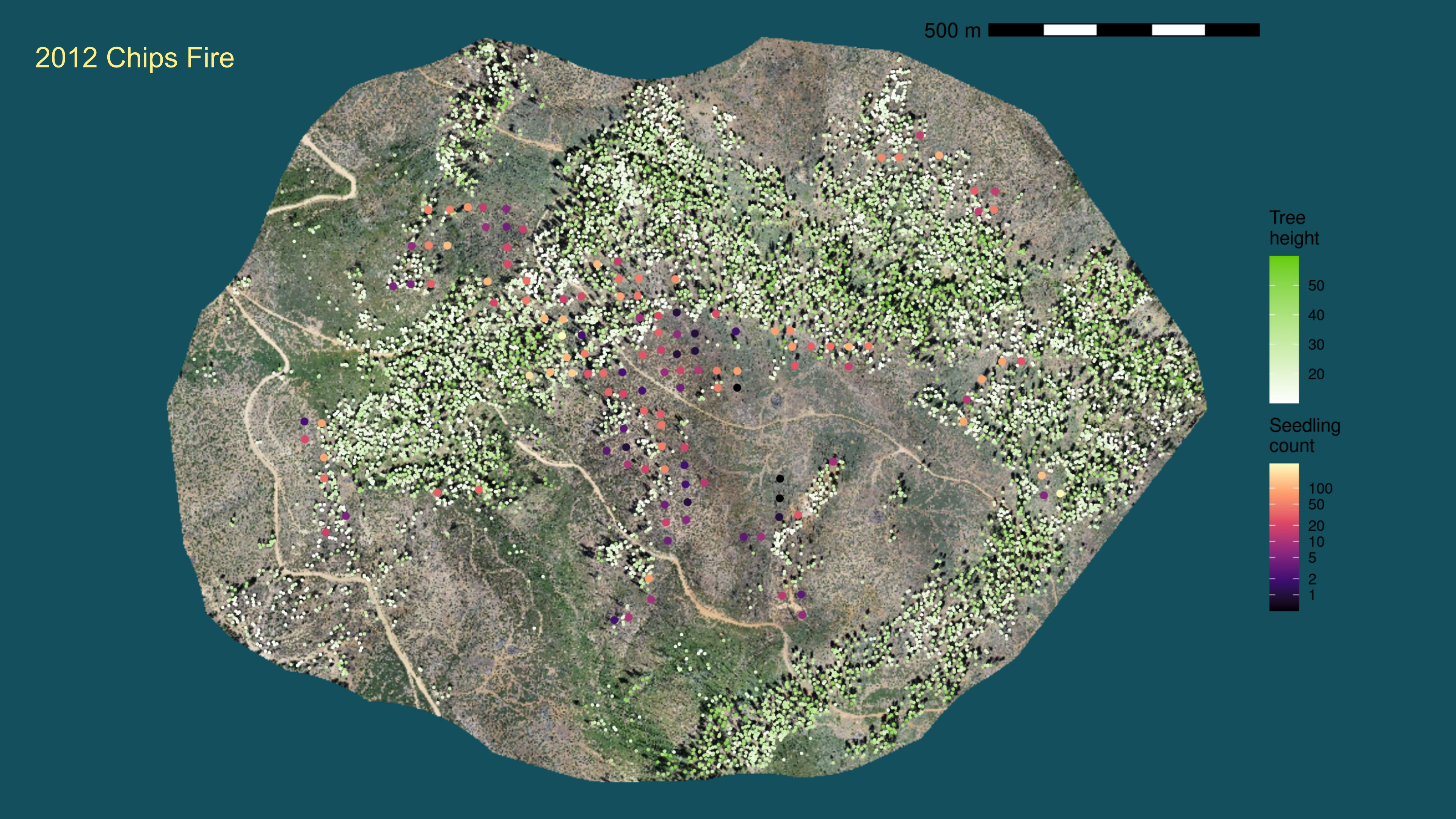
80 m altitude, oblique (25°) camera



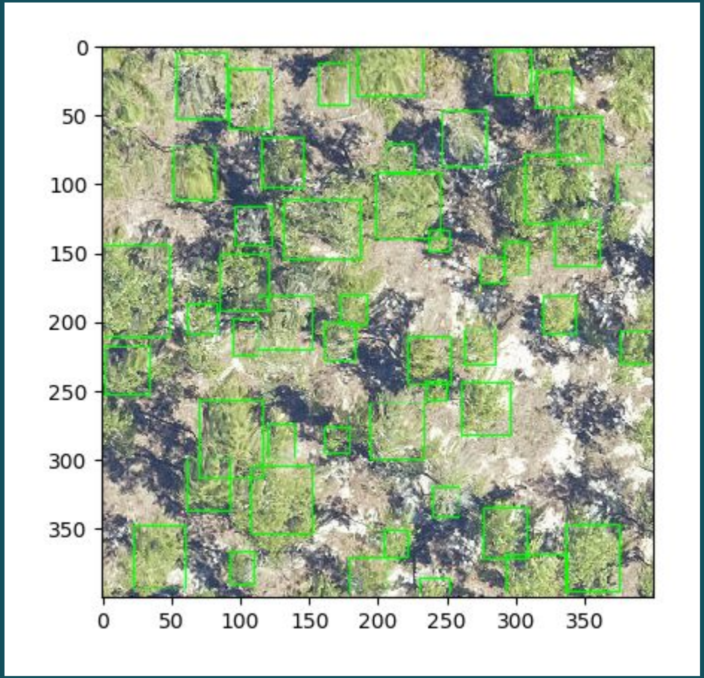
EasyIDP: github.com/UTokyo-FieldPhenomics-Lab/EasyIDP

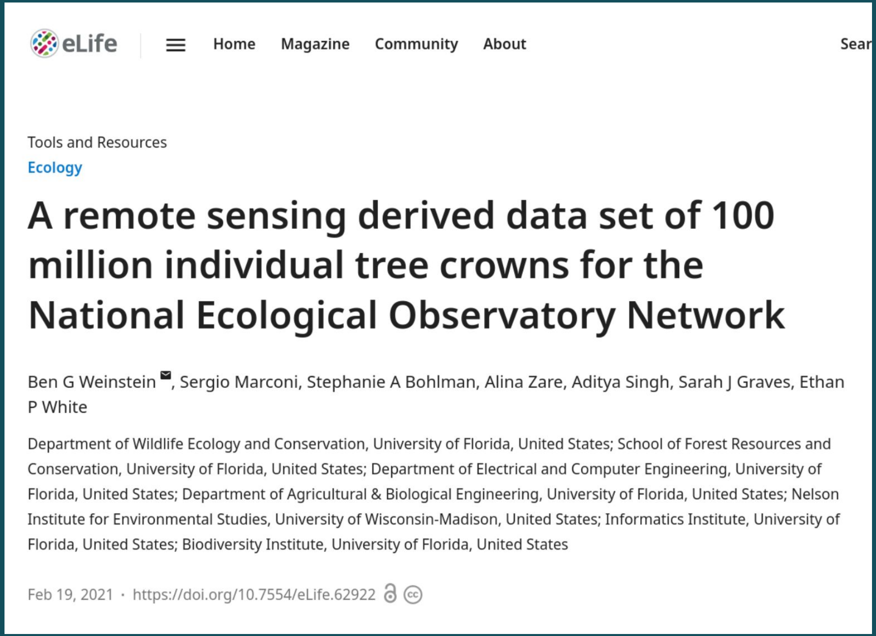


Species	Precision	Recall	F score
cedar	0.83	0.75	0.79
fir	0.87	0.96	0.91
pine	0.94	0.95	0.94


2012 Chips Fire
500 m
Tree height
50
40
30
20
Seedling count
100
50
20
10
5
2
1

Computer vision for tree detection

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Tools and Resources

Ecology

A remote sensing derived data set of 100 million individual tree crowns for the National Ecological Observatory Network

Ben G Weinstein, Sergio Marconi, Stephanie A Bohlman, Alina Zare, Aditya Singh, Sarah J Graves, Ethan P White

Department of Wildlife Ecology and Conservation, University of Florida, United States; School of Forest Resources and Conservation, University of Florida, United States; Department of Electrical and Computer Engineering, University of Florida, United States; Department of Agricultural & Biological Engineering, University of Florida, United States; Nelson Institute for Environmental Studies, University of Wisconsin-Madison, United States; Informatics Institute, University of Florida, United States; Biodiversity Institute, University of Florida, United States

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Python package DeepForest: Weinstein et al.

Individual tree-based mapping for post-fire planning?

Current limitation

- Small drone flight footprints

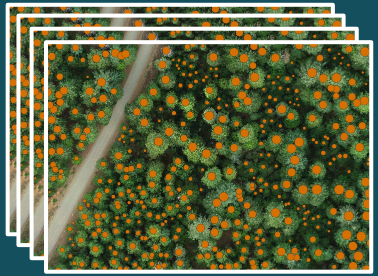
Current applications

- Inform existing tools
- Areas of special concern
- Complement to field surveys

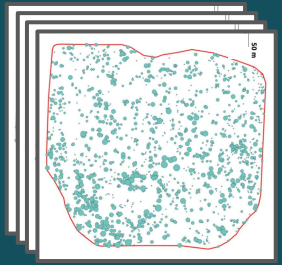
Emerging applications

- Increasing availability of lidar
- Multiple efforts for region-wide tree mapping
- Improving satellite resolution (spatial and spectral)

Open Forest Observatory



Drone-derived inventories



Field-based stem maps

Drone-based mapping tools

www.openforestobservatory.org

OFO Team: Derek Young, Michael Koontz, Tyson Swetnam, Jeff Gillan, Megan Korte, Michelle Garcia, Steven DePaschalis, Saira Erfan, Hannah Potts, Oren Nardi. **Starting soon:** David Russell, Christopher Wong

Thank you!

Collaborators
Andrew Latimer
Nina Venuti
Michael Koontz
Jonah Weeks
Marc Meyer
Kevin Welch

Modeling framework
Philippe Marchand

Field technicians
Ian Nilson
Hannah de la Calle
Maaike Wielenga
Landin Noland
Sabrina Denton
Sam Vaillancourt
Clancy McConnell
Bobby Arlen

Contact:
Derek Young
djyoung@ucdavis.edu

CALIFORNIA DEPARTMENT OF FORESTRY & FIRE PROTECTION CAL FIRE SINCE 1885

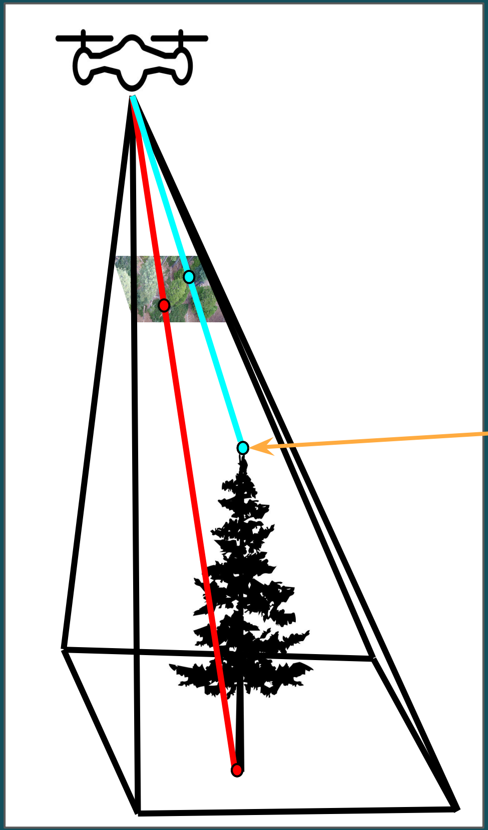
CALIFORNIA CLIMATE INVESTMENTS Cap and Trade Dollars at Work

NSF

UC DAVIS UNIVERSITY OF CALIFORNIA

Species ID

Back-projection of tree location onto each drone photo



Enlarge Detail View

An Object-Based Image Analysis Method for Enhancing Classification of Land Covers Using Fully Convolutional Networks and Multi-View Images of Small Unmanned Aerial System

by Tao Liu [1,2,*] and Amr Abd-Elrahman [1,2]

1 School of Forest Resources and Conservation, University of Florida, Gainesville, FL 32611, USA

2 Gulf Coast Research Center, University of Florida, Plant City, FL 33563, USA

* Author to whom correspondence should be addressed.

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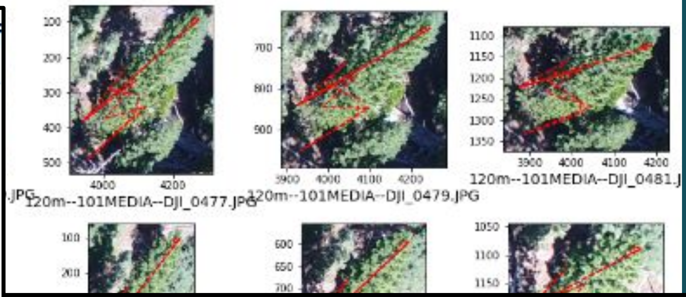

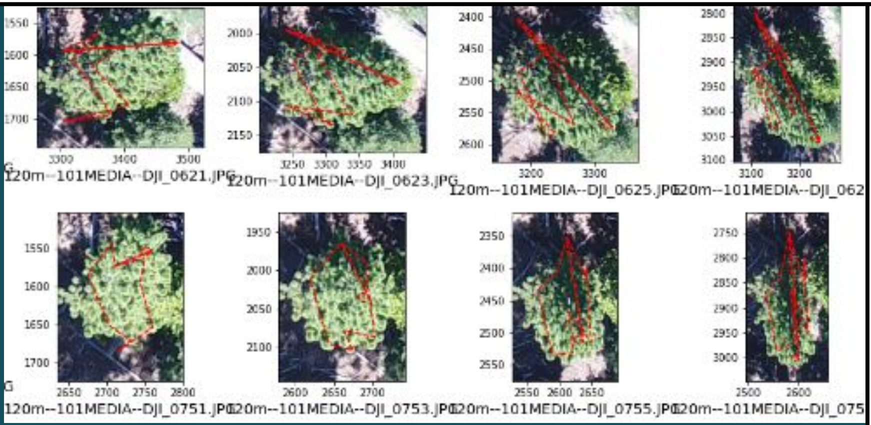

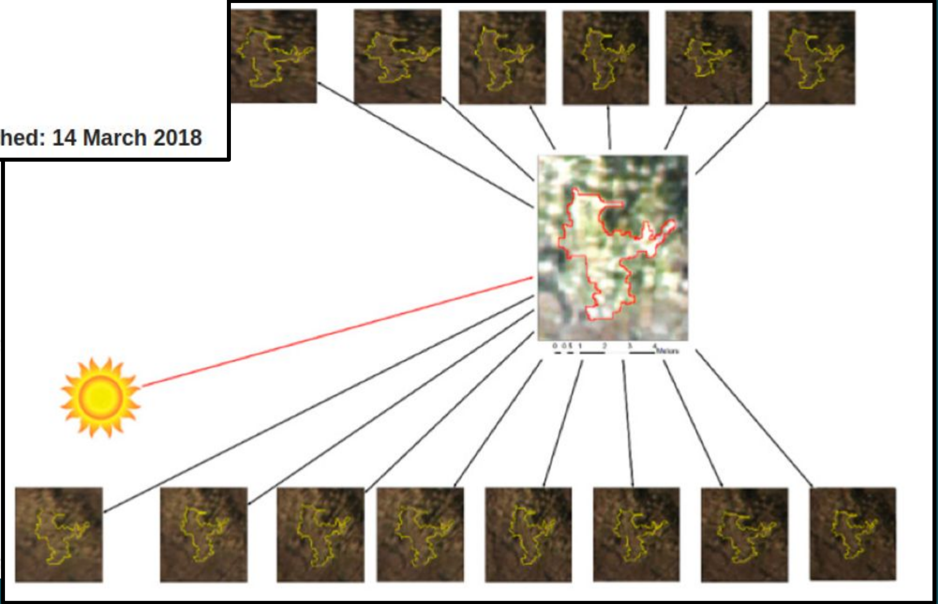

EasyIDP: github.com/UTokyo-FieldPhenomics-Lab/EasyIDP