Modeling Environmental Factors Related to Drought-Induced Tree Mortality based on Lidar and Hyperspectral Imagery

Master's Thesis Defense Presentation

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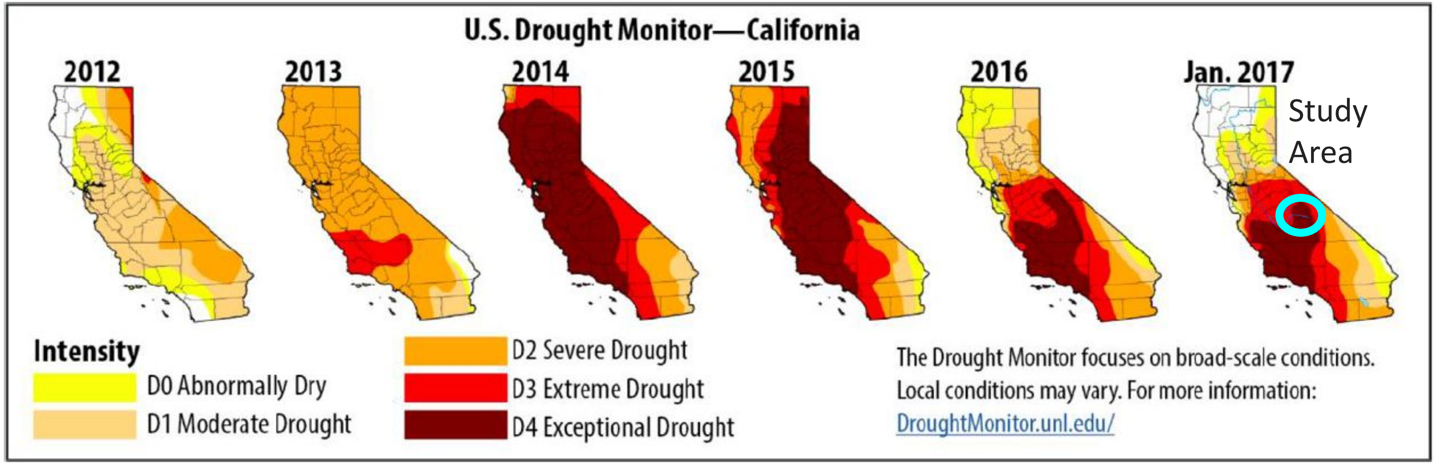
Tuesday, July 13th, 2021
11am PST
https://pdx.zoom.us/j/85068239434

Introduction:

Drought-induced tree mortality



From 2012 - 2015, California experienced lowest four-year precipitation levels since the late 19th century while 2014 and 2015 were the hottest years on record (Chang and Bonnette 2016).

129 million trees have died in California since 2010 (US Forest Service 2017a).

A combination of warm temperatures and water stress have made trees more susceptible to bark beetle outbreaks, which together have led to one of the worst epidemics of tree mortality in the Sierra Nevada (US Forest Service 2017a).

Introduction:
Bark beetles

Population levels of bark beetles oscillate periodically, often reaching high densities and causing extensive tree mortality when favorable forest and climatic conditions coincide.

During the past decade, tree mortality caused by bark beetles has increased in spruce, lodgepole, pinyon-juniper, and ponderosa forests.

This increase is correlated with shifts in temperature and increased water stress, which create conditions within trees that are favorable to beetle survival and growth.

https://www.fs.fed.us/research/invasive-species/insects/bark-beetle.php

https://apps.fs.usda.gov/r6_decaid/views/western_pine_beetle.html

https://www.latimes.com/local/california/la-me-sierra-dead-trees-20170128-story.html

https://www.montanabusinessquarterly.com/recovering-from-the-mountain-pine-beetle/

Introduction:

Why care?

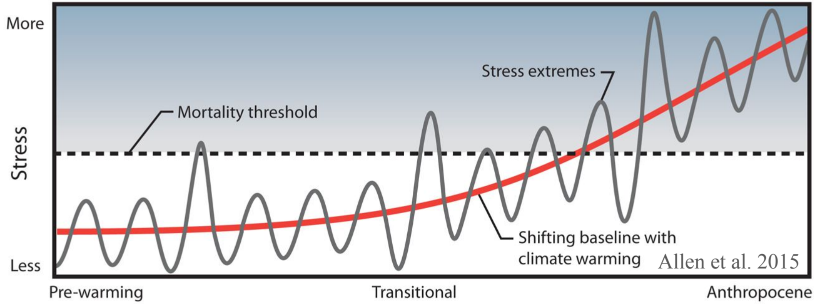
These forests provide:

- Wildlife habitat
- Carbon storage and sequestration
- Water supply
- Timber products
- Ecotourism and recreation

(Adams et al. 2012, Allen 2007, Bigler et al. 2005).

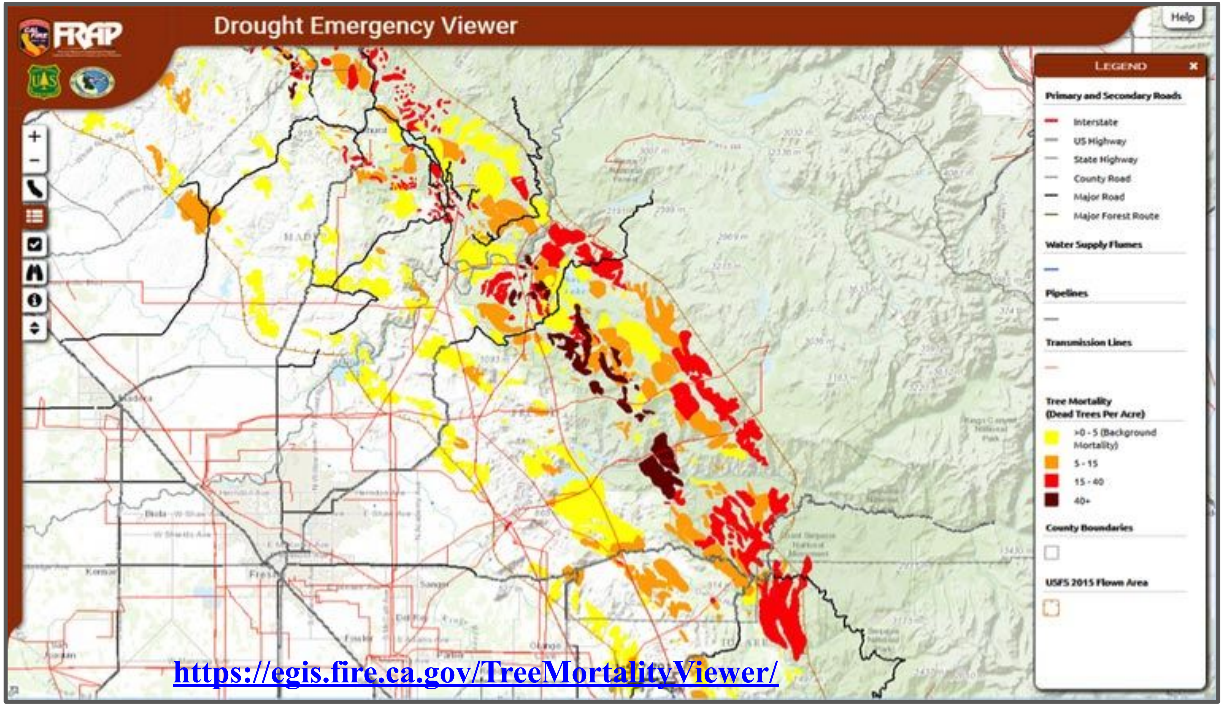
Groupings of dead trees and dropped needles and branches pose significant wildfire threat (US Forest Service 2017b).

Species-specific mortality could indicate possible shift in community composition over time (Paz-Kagan et al. 2019).



Introduction:

What is being done?



https://egis.fire.ca.gov/TreeMortalityViewer/

Ground-based methods can be time-consuming and costly.

The USFS Aerial Detection Survey (ADS) uses Google Earth satellite imagery and aerial camera imagery to create sketch maps of areas containing tree mortality, defoliation, and other damage over the Sierra.

Introduction:

Research Question

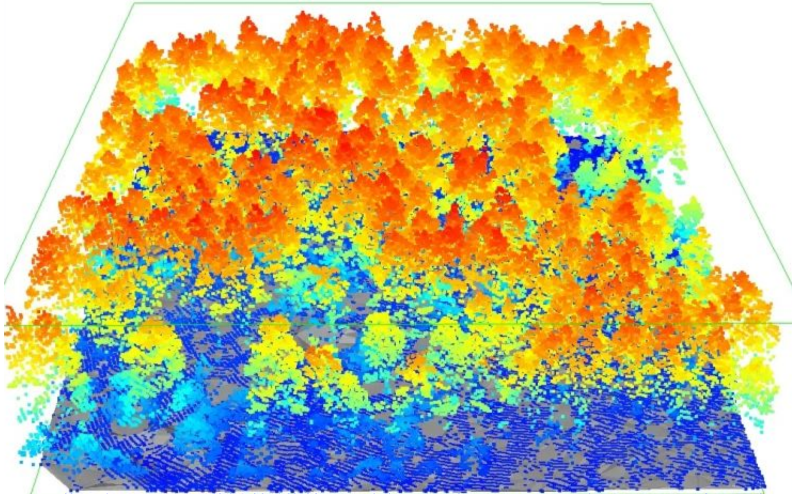
This research uses publicly available remote sensing data to map drought-induced tree mortality and assess areas and genuses of high risk by addressing the following research question:

> **How did interacting site-specific environmental factors (relating to topography, substrate, and stand characteristics) mediate tree mortality in the Central Sierra Nevada during the 2012-2016 California drought?**

Literature Review:

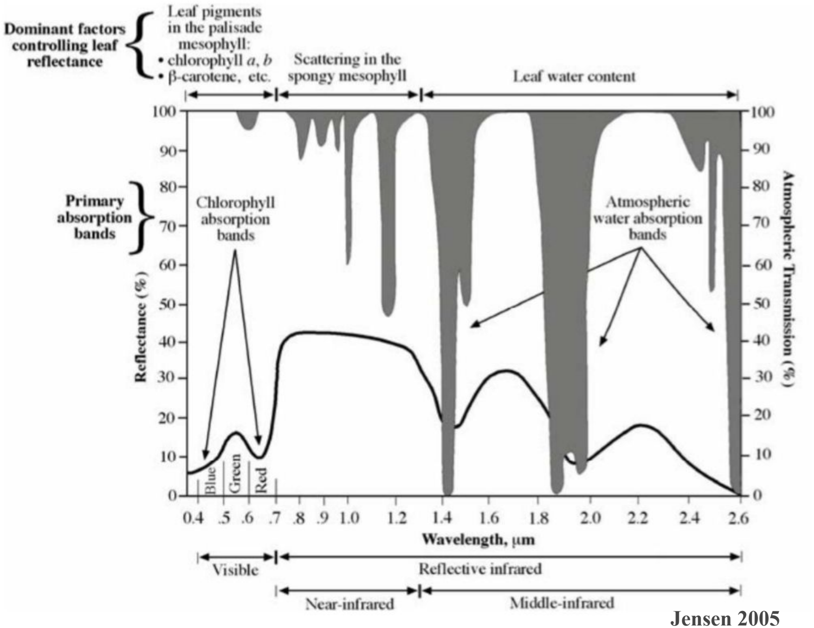
Remote sensing in vegetation monitoring

<u>Active</u>: Light detection and ranging (**Lidar**)



https://rapidlasso.com/2014/11/04/rasterizing-perfect-canopy-height-models-from-lidar/

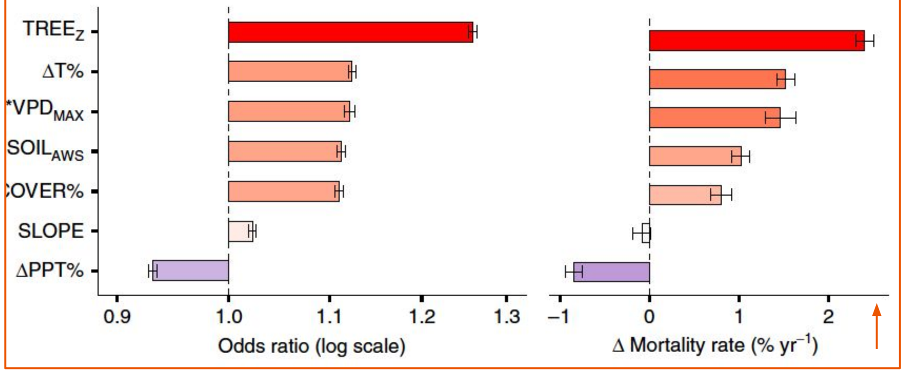
<u>Passive</u>: Hyperspectral Imaging (**HSI**)

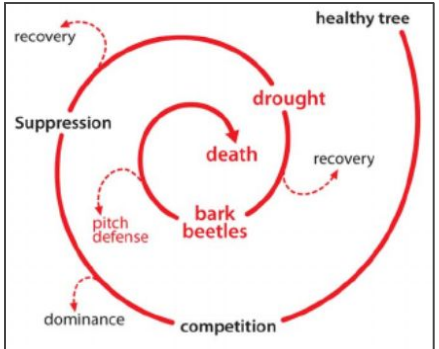


Jensen 2005

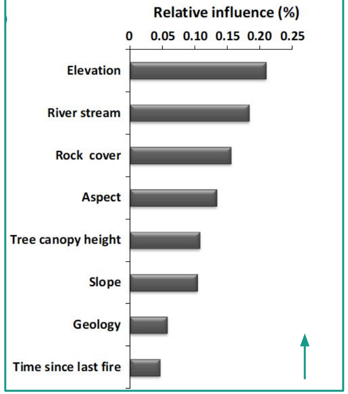
Literature Review:

Factors affecting tree mortality

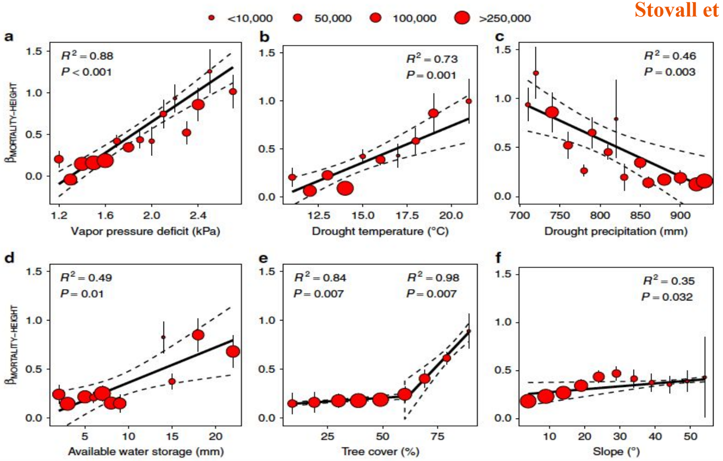




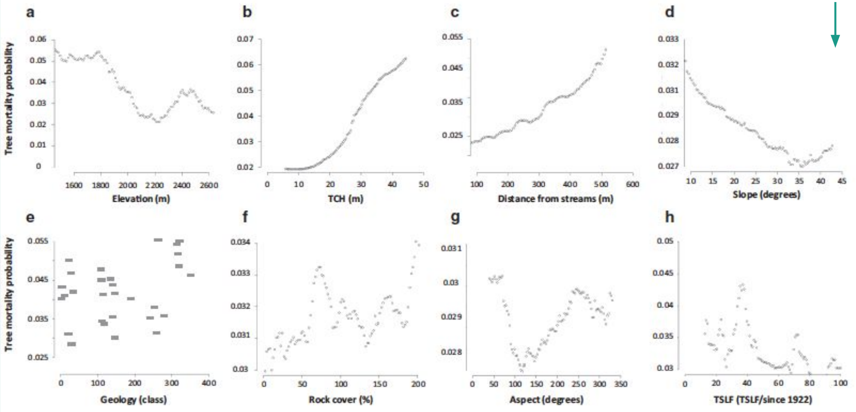
Allen et al. 2015



Stovall et al. 2019

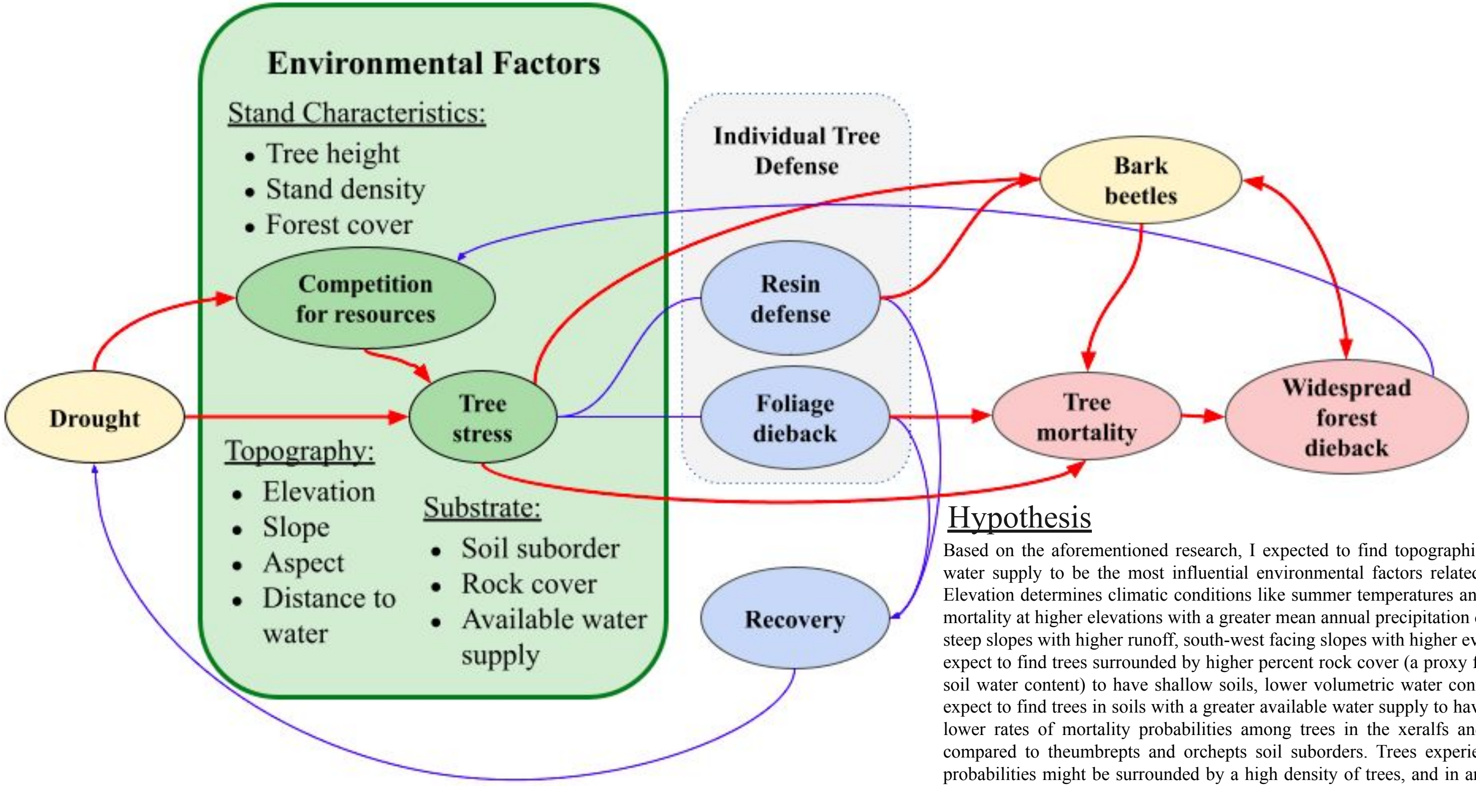


Paz-Kagan et al. 2019



Literature Review:

Conceptual framework of factors influencing tree mortality based on existing literature



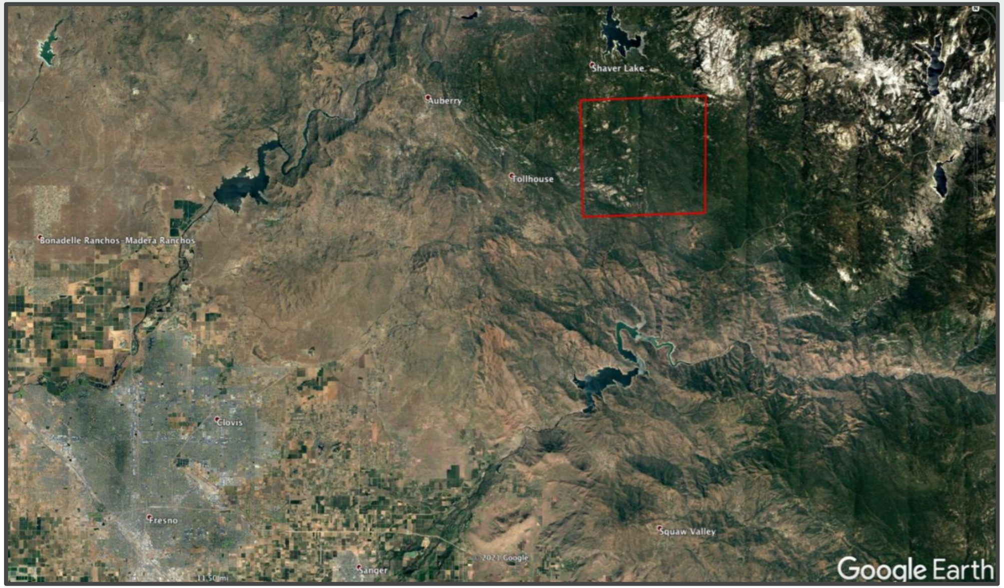
Hypothesis

Based on the aforementioned research, I expected to find topographic, substrate, and tand characteristics affecting a tree's water supply to be the most influential environmental factors related to drought-induced tree mortality in the study area. Elevation determines climatic conditions like summer temperatures and winter rainfall. Thus, I expect to find higher rates of mortality at higher elevations with a greater mean annual precipitation deficit. I also expect to find higher rates of mortality on steep slopes with higher runoff, south-west facing slopes with higher evapotranspiration rates, and trees further from streams. I expect to find trees surrounded by higher percent rock cover (a proxy for soil depth which can be used to estimate volumetric soil water content) to have shallow soils, lower volumetric water content, and lower rates of mortality. For these reasons, I expect to find trees in soils with a greater available water supply to have higher mortality probabilities. I also expected to find lower rates of mortality probabilities among trees in the xeralfs and xerolis soil suborders used to lower water content compared to theumbrepts and orchepts soil suborders. Trees experiencing more competition and thus a higher mortality probabilities might be surrounded by a high density of trees, and in areas with high percent forest cover. I also expect taller trees to have greater water needs and to be associated with higher rates of mortality probability. Bark beetles have been known to attack Pinus ponderosa, so I expected to find higher mortality probabilities among pines in the study area.

Methods:

Study Area

- Located 35 mi northeast of Fresno, CA
- In the mid elevation range (1000 m - 1400 m) of Sierra National Forest

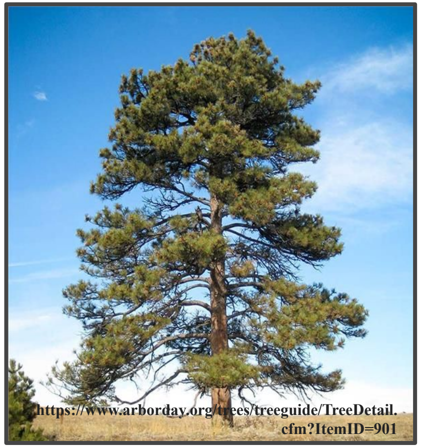


Dominant Vegetation:

https://www.neonscience.org/field-sites/soap

California incense cedar

Ponderosa pine



California black oak

Canyon live oak

Mariposa manzanita

Methods:

Workflow diagram

Remote Sensing Data

Downloaded from https://www.neonscience.org/data

Lidar:

1. Create **DEM** and DSM from las point cloud
2. Create **CHM**: DSM minus **DEM**
3. Identify and segment **tree crowns**

HSI:

1. Mosaic 100 1km by 1km, 426-band HSI reflectance tiles
2. Remove shadows & noise bands (426 to 341 bands)
3. Reduce 341 HSI bands to 30 **PC** bands
4. Choose 13 **PC** bands as inputs to the **Classifiers**

Key Terms:

Lidar: Light detection and ranging

DEM: Digital elevation model

DSM: Digital surface model

CHM: Canopy height model

HSI: Hyperspectral image

PC: Principal component

Image Classifications

Used 1 **CHM** and 13 **PCs** to predict pixel class

Live/Dead Classifier:

(1) **Live tree,** **Live pixels** (2) **Gray-stage**, (3) **Red-stage**, (4) Groundcover, (5) Soil, (6) **Rock**, (7) Shrub

Genus Classifier:

(1) Oak
(2) Pine
(3) Cedar
(4) Other

Live/Dead and Genus tree crown attribution:

- Assign **tree crowns** a **0** (**Live**) or **1** (**Dead - Gray-stage / Red-stage**)
- Assign **Live** tree crowns a Genus

Tree Mortality Modeling

Live/Dead tree crowns (Y) ~ Environmental variables (X)

Environmental variable attribution:

- *Topography* from **DEM**
- *Canopy structure* from **tree crowns** and forest cover (**Live** plus **Dead** pixels divided by total pixels)
- *Substrate* from rock cover (**Rock** pixels divided by total pixels) and USDA Soil Data Viewer

Methods:

Lidar

1. Created DEM and DSM from lidar point cloud with lidR package in R
2. CHM = DSM - DEM
3. Identified tree tops and segmented tree crowns from CHM with Forest Tools package in R

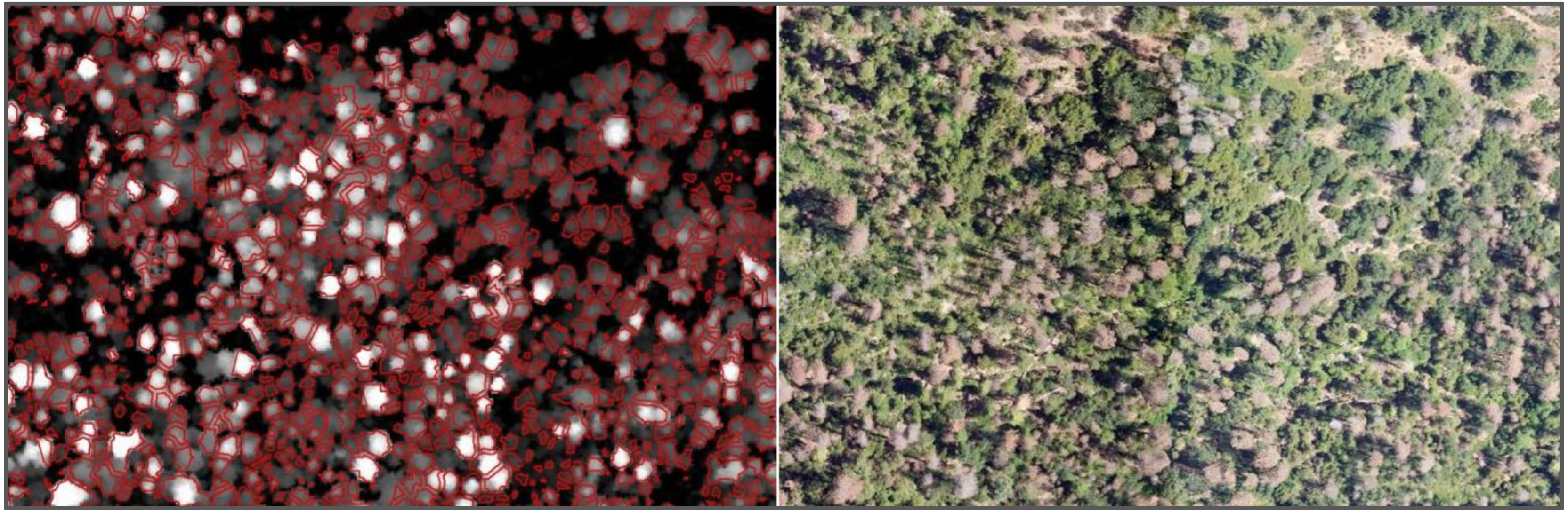
Key Terms:

Lidar: Light detection and ranging

DEM: Digital elevation model

DSM: Digital surface model

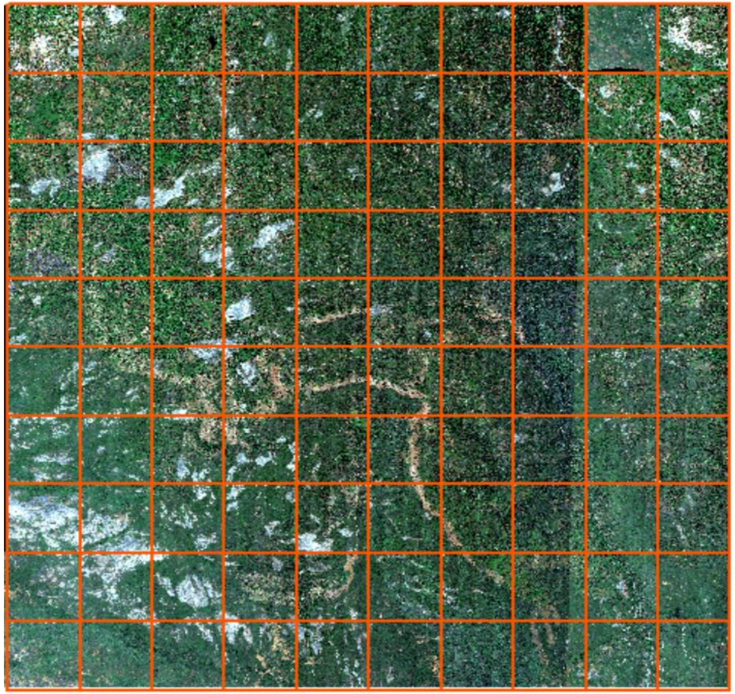
CHM: Canopy height model



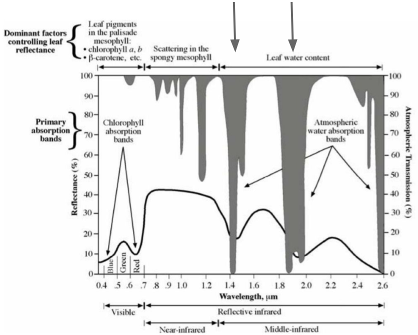
Methods: HSI

Key Terms:
HSI: Hyperspectral image
PC: Principal component

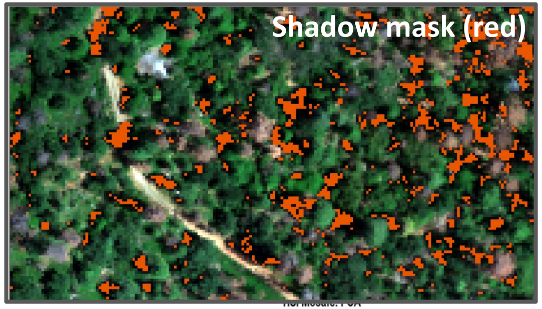
1. Mosaiced 100 1km by 1km, 426-band HSI reflectance tiles



2. Removed atmospheric absorption bands and masked shadows

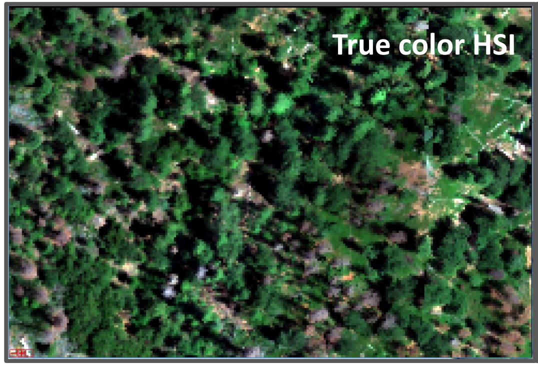


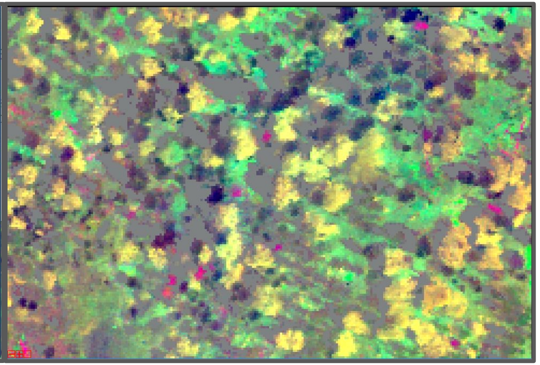
Jensen 2005



3. Reduced 341 HSI bands to 30 PC bands and chose 13 as inputs to the image classifications

PCA 6,5,2

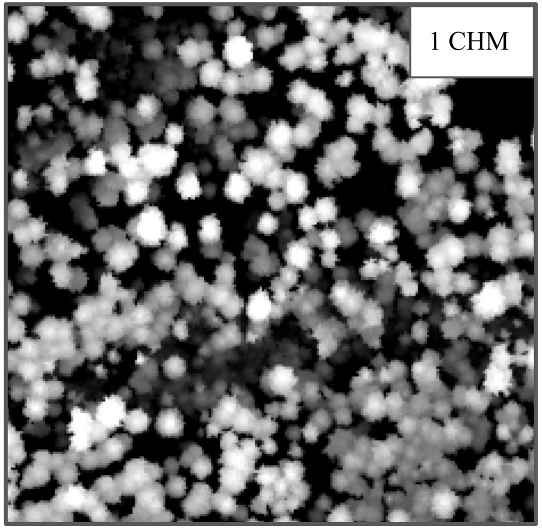




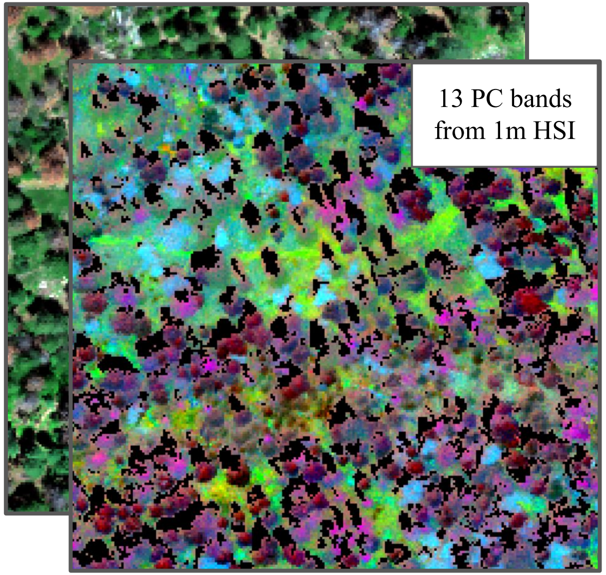
Methods:

Image Classifications

Raster Inputs:



+



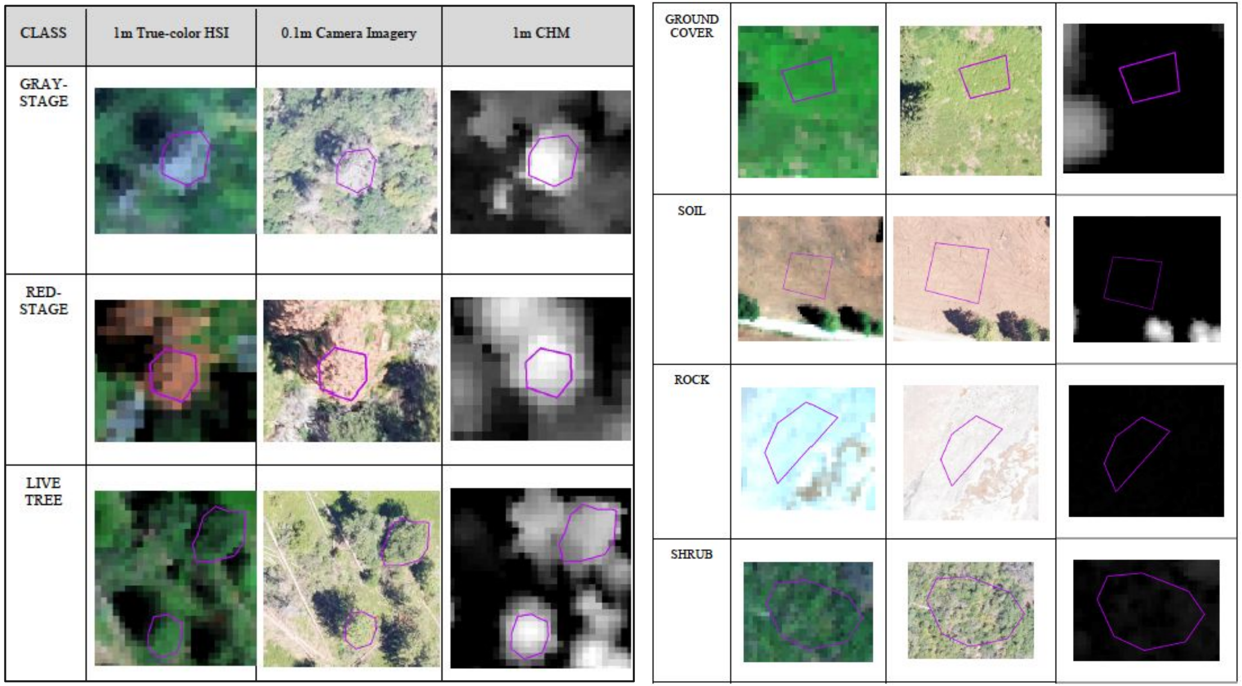
Training:

Pixels to be chosen from raster inputs primarily referencing high-resolution camera imagery and survey points from Weinstein et al. 2021.

Methods:

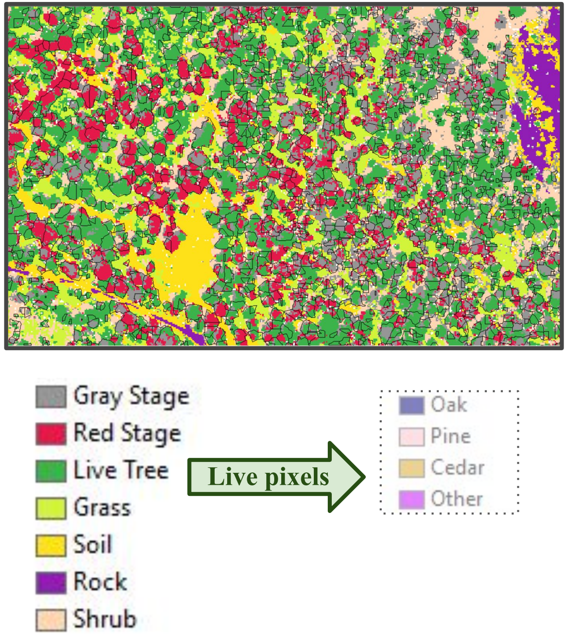
Live/Dead Classification

Image Interpretation Key:



- Set aside 70% of the polygons for each class for model training and 30% for model validation
- Extracted training polygon pixel values from the input rasters with the ‘raster’ package in R
- Trained and tested the random forest classifier with the ‘ranger’ package in R

Live/Dead Classification

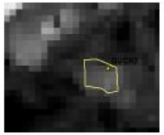
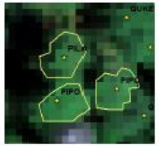
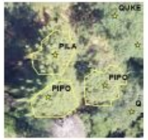
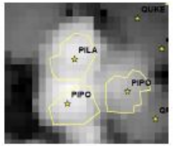
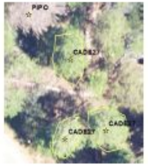
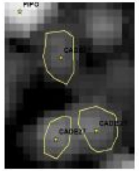
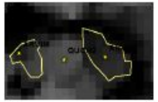


- Assigned lidar-derived tree crowns a 0 (Live) or 1 (Dead: Gray- or Red-Stage) attribute based on the most frequently occurring class pixel in a polygon

Methods:

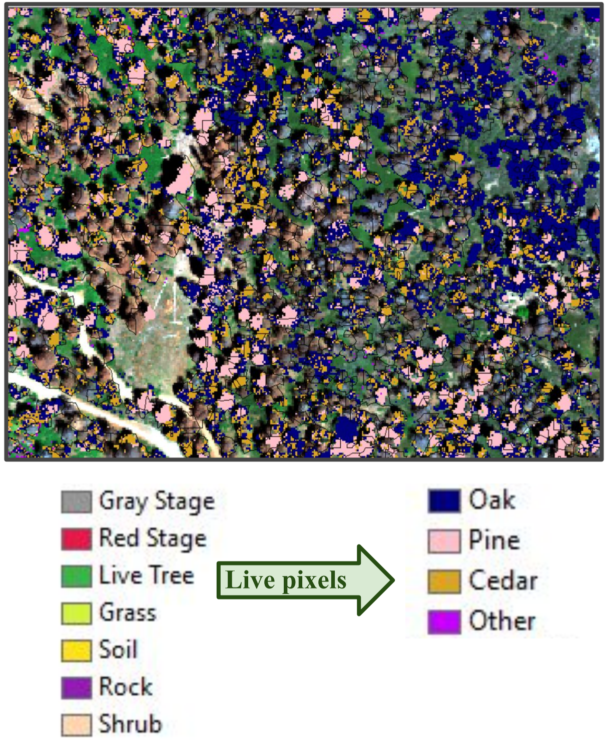
Genus Classification

Image Interpretation Key:

OAK QUCH2 - Quercus chrysolepis Liebm.			
PINE PILA - Pinus lambertiana Douglas PIPO - Pinus ponderosa Lawson & C. Lawson			
CEDAR CADE27 - Calocedrus decurrens (Torr.) Florin			
OTHER ARVIM - Arctostaphylos viscida Parry ssp. mariposa (Dudley) P.V. Wells			

- Set aside 70% of the polygons from each class for model training and 30% for validation
- Extracted training polygon pixel values from the input rasters using the 'raster' package in R
- Trained and tested the random forest classifier using the 'ranger' package in R
- Assigned the live attributed tree crowns an Oak, Pine, Cedar, or Other genus based on the most frequently occurring class pixel in a polygon

Genus Classification



Methods:

Tree Mortality Modeling - Random Forest Regression

- Each live (oak, cedar, pine) and dead (red-stage, gray-stage) tree was attributed with environmental variables related to topography, substrate, and stand characteristics.
- Paz Kagan et al. 2017 found climate variables to be correlated with each other and elevation.

Environmental Factors	Units	Spatial Resolution	Source
Topography			
Elevation	m	1m	Lidar point cloud
Slope	°	1m	Digital Elevation Model
Aspect	°	1m	Digital Elevation Model
Distance from streams	m	1m	Digital Elevation Model
Stand Characteristics			
Tree height	m	1m	Canopy Height Model
Forest cover	%	100 sq km	Live/Dead Classification
Density	count per 100 sq km	100 sq km	Canopy Height Model
Substrate			
Rock cover	%	100 sq km	Live/Dead Classification
Soil Suborder	classes	Vector	USDA Web Soil Survey 2019
Available Water Supply	cm	Vector	USDA Web Soil Survey 2019
Organic Matter content	cm	Vector	USDA Web Soil Survey 2019
Water pH	cm	Vector	USDA Web Soil Survey 2019

Results:

Attributed tree crowns in the study area

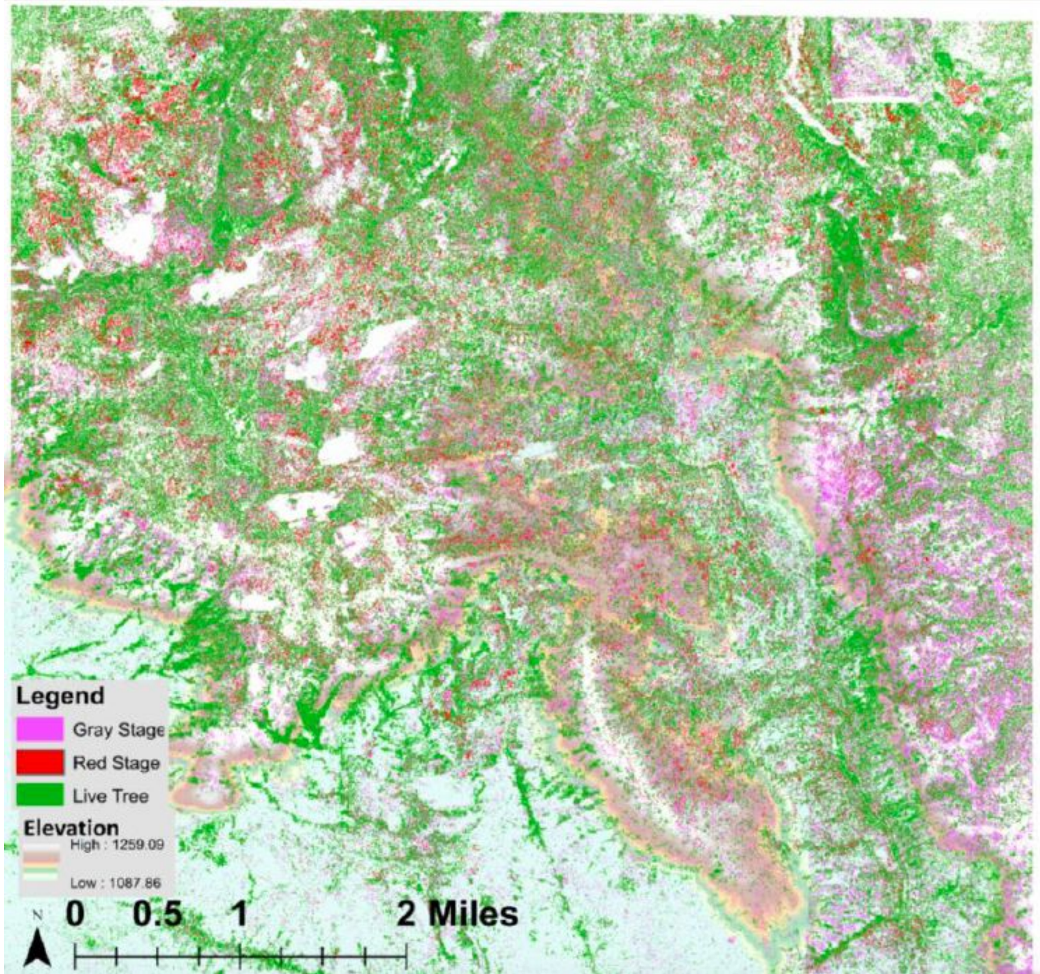
- 471,791 lidar-derived tree crowns with **live** tree pixel majorities
- 77,192 lidar-derived tree crowns with **red-stage** mortality tree pixel majorities
- 219,699 lidar-derived tree crowns with **gray-stage** mortality tree pixel majorities

Live/Dead Confusion Matrix

Live/Dead	Gray-Stage	Red-Stage	Live	Ground Cover	Soil	Rock	Shrub	**Count**	**UA**
Gray-Stage	856	105	1	0	0	0	32	994	86.1
Red-Stage	10	990	11	0	4	0	14	1029	96.2
Live	3	1	2179	3	0	0	9	2195	99.2
Groundcover	0	0	0	741	11	0	0	752	98.5
Soil	0	0	0	1	954	0	0	955	99.8
Rock	0	0	0	0	0	1572	0	1572	100
Shrub	6	0	169	18	3	3	4142	4341	95.4
Count	875	1096	2360	763	972	1575	4197	**OA**	**κ**
PA	97.8	90.3	92.3	97.1	98.1	99.8	98.6	**96.48**	**0.95**

Genus Confusion Matrix

Genus	Oak	Pine	Cedar	Other	**Count**	**UA**
Oak	624	12	45	18	699	89.3
Pine	7	350	29	0	386	90.7
Cedar	74	41	329	6	450	73.1
Other	8	0	15	785	808	97.2
Count	713	403	418	809	**OA**	**κ**
PA	87.5	86.8	78.7	97.0	**89.12**	***0.85***



Results:

Tree Mortality Modeling - Random Forest Regression

Response:

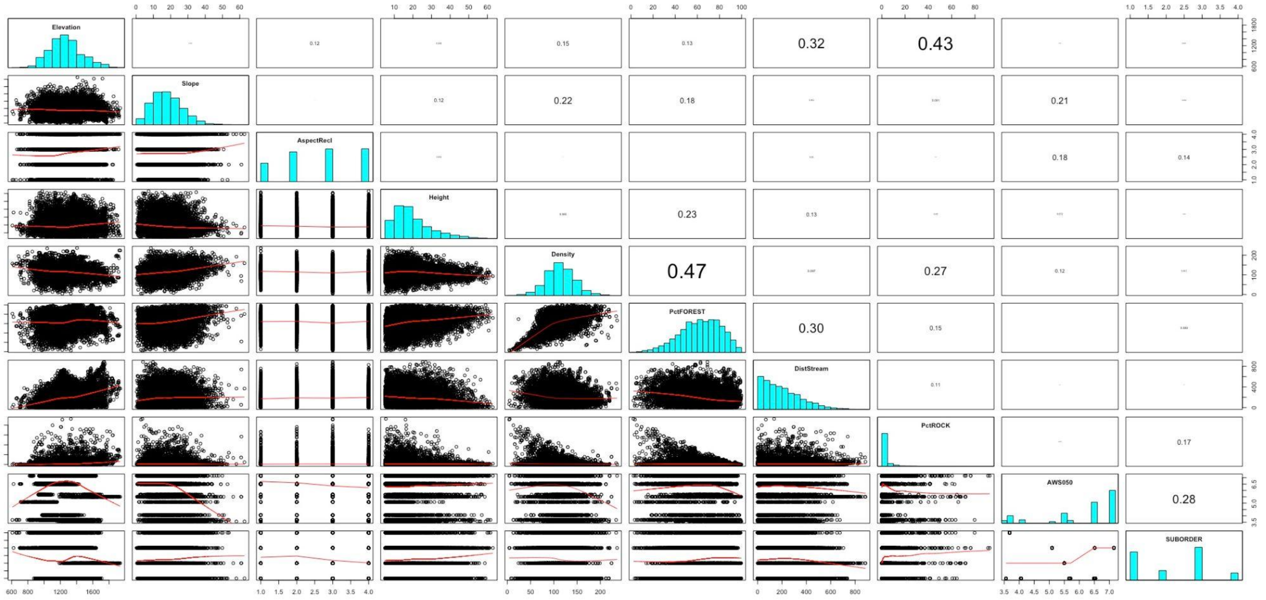
Tree crown assigned **0 (live)** or **1 (dead)**

Predictors:

	Environmental Factor	Environmental Variable
1.	Elevation	Elevation
2.	Slope	Slope
3.	Aspect	AspectRecl
4.	Height	Height
5.	Density	Density
6.	Forest cover	PctFOREST
7.	Rock cover	PctROCK
8.	Distance to streams	DistStream
9.	Available water supply	AWS050
10.	Soil Suborder	SUBORDER
11.	Organic matter content*	omr
12.	Water pH*	pH

* removed due to multicollinearity

Environmental Variable Correlation Matrix:



RF parameters:

nTree: 200

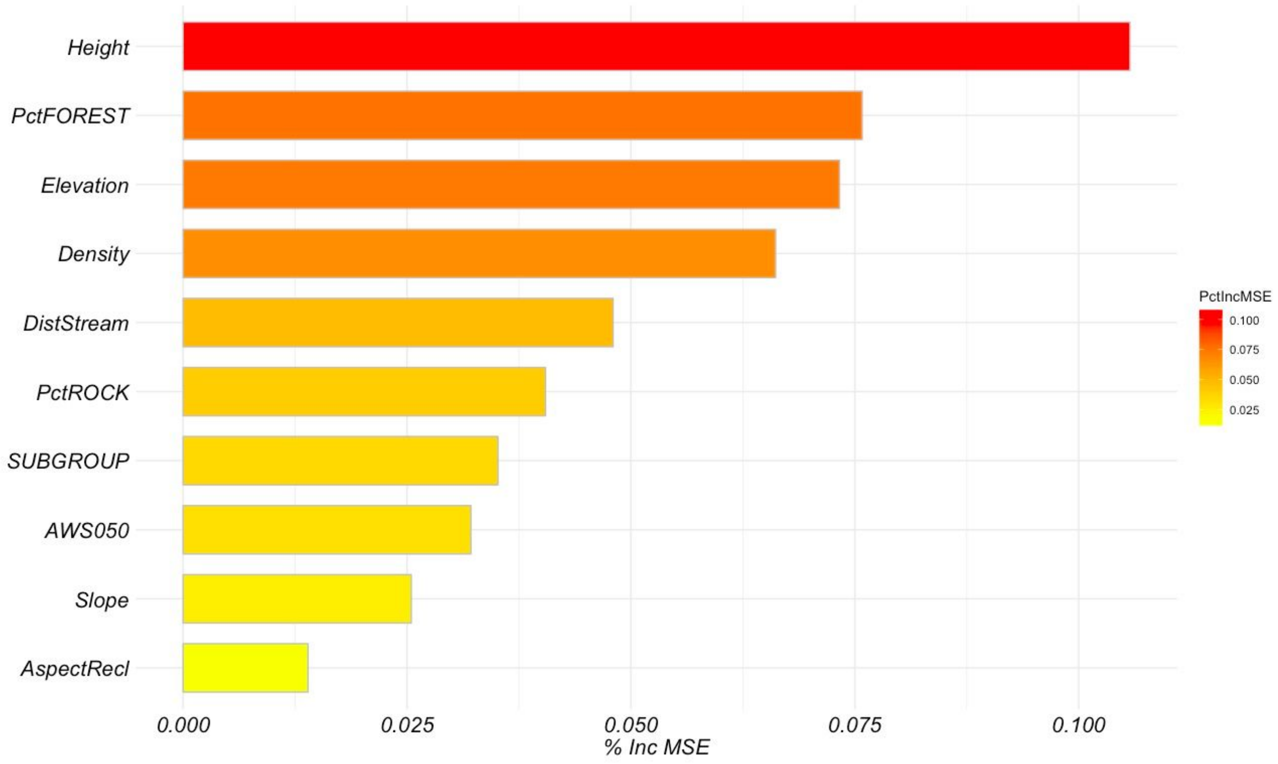
mTry: 3

Final model R-squared:

0.41

Results:

Random Forest Variable Importance



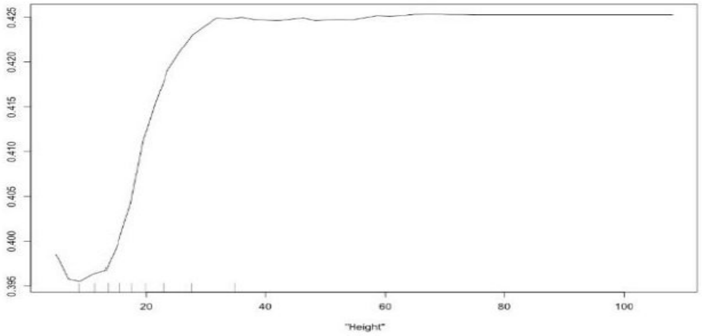
Variable Importance:

- By percent increase in Mean Square Error

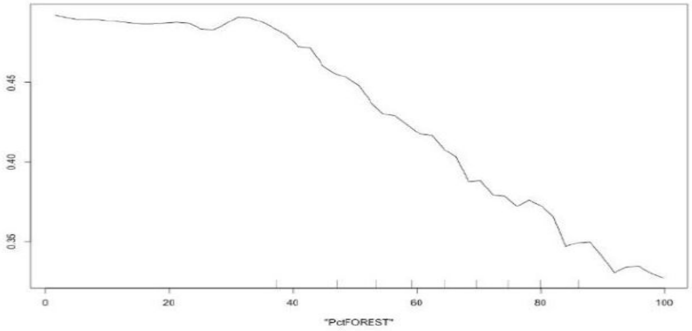
Results:

Partial Dependence (1 of 2)

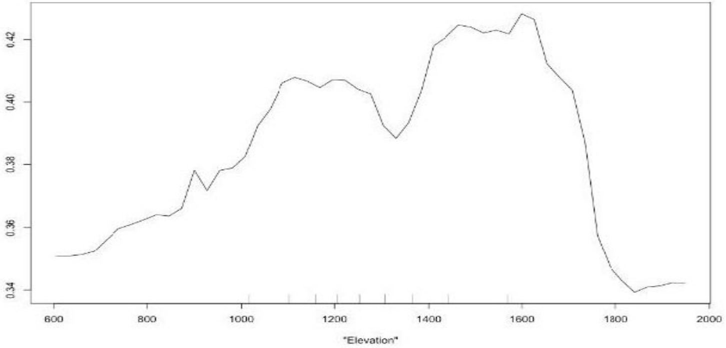
Partial Dependence on Height



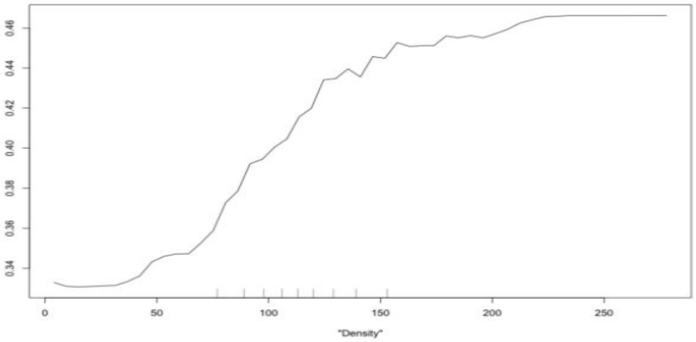
Partial Dependence on Forest cover



Partial Dependence on Elevation



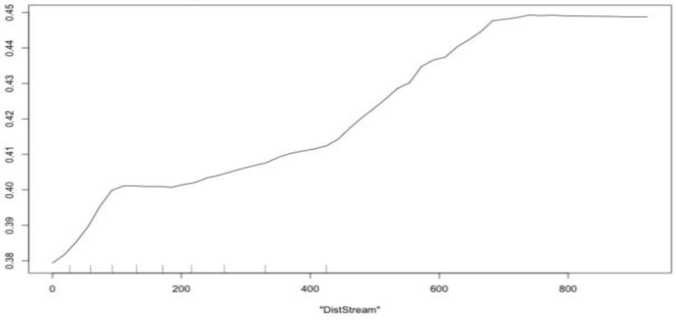
Partial Dependence on Density



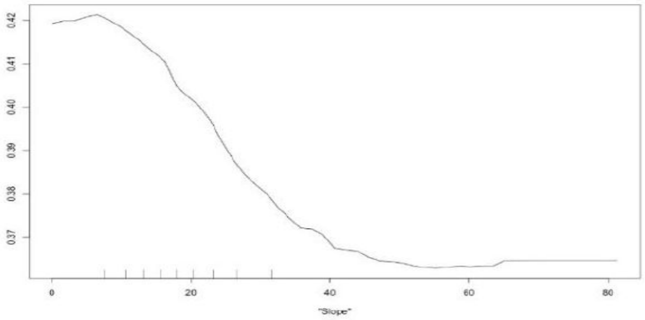
Results:

Partial Dependence (2 of 2)

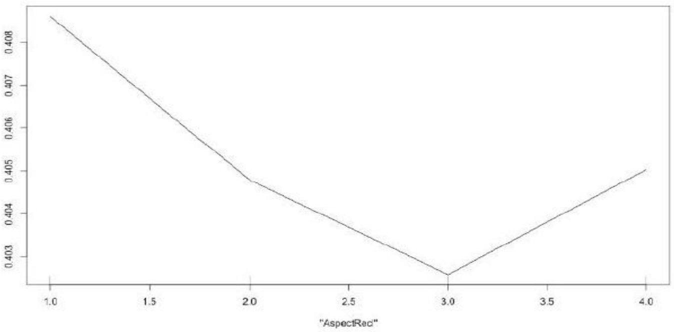
Partial Dependence on Distance to streams



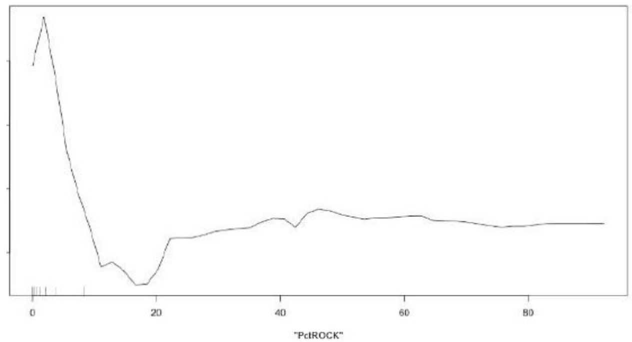
Partial Dependence on Slope



Partial Dependence on Aspect



Partial Dependence on Rock cover



Results:

Genus-specific mortality

I applied random forest model to predict the probability of mortality for each tree.

Average mortality probability:

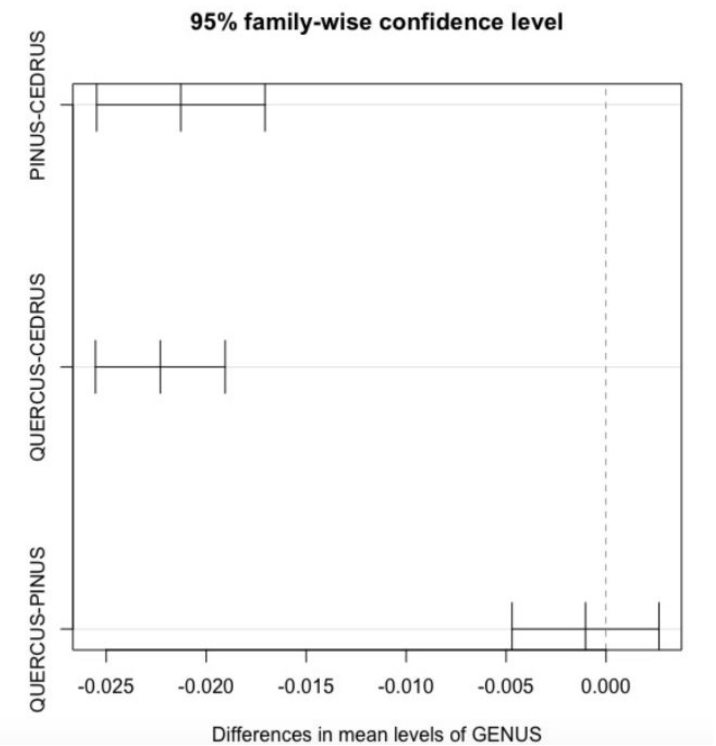
- Oak: 0.39
- Pine: 0.43
- Cedar: 0.26

ANOVA p-value < 0.05:

- Mean mortality probability is significantly different between species

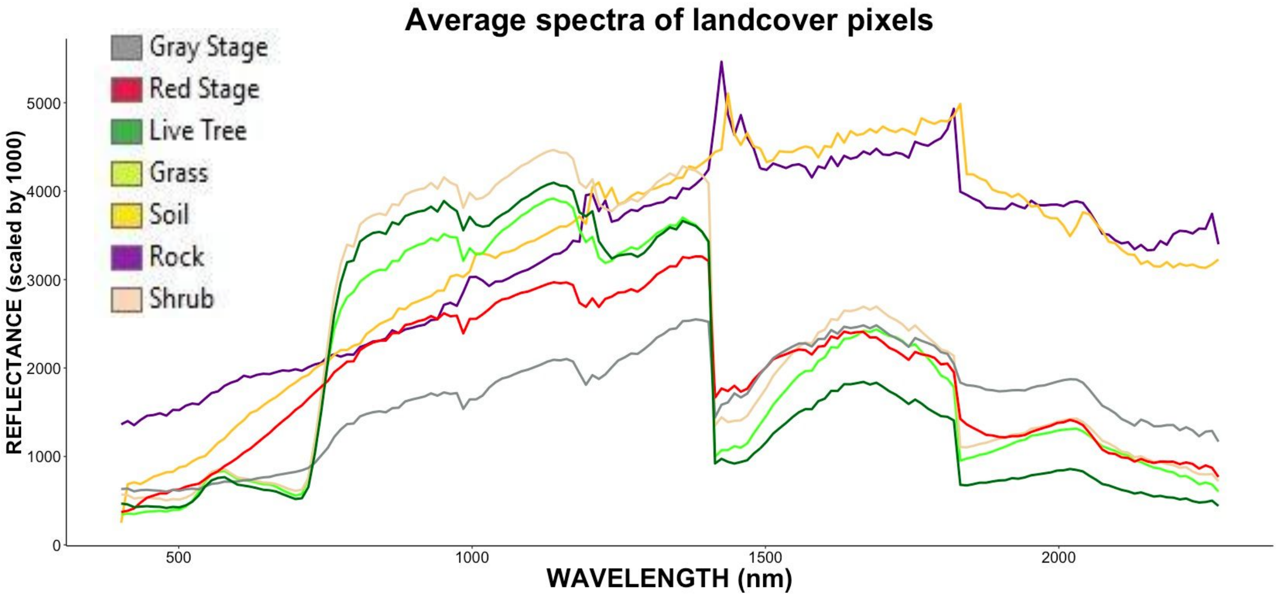
Tukey's honestly significant difference (HSD) post hoc test:

- Difference between oak-pine genus pair group means is not significantly different
- Difference between oak-cedar and pine-cedar pair groups is significantly different



Discussion:

Image Classifications



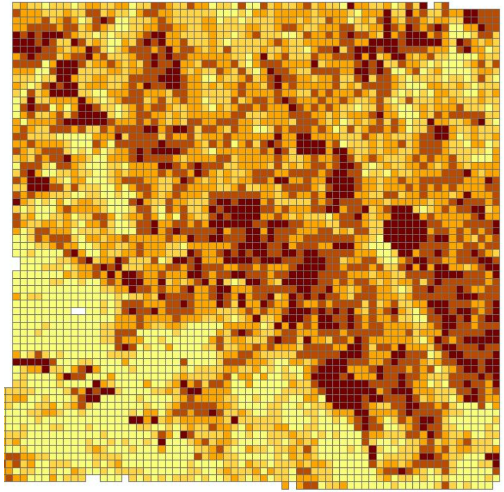
Why lidar and HSI?

- Shrub vs Live Tree
- Grass vs Live Tree
- Soil vs Red-Stage

Discussion:

Predicting tree mortality

- Predicting a tree's probability of mortality was low
  - R-squared = 0.41
- Better able to predict mortality fraction: the number of dead trees divided by the total trees per plot
  - R-squared = 0.86

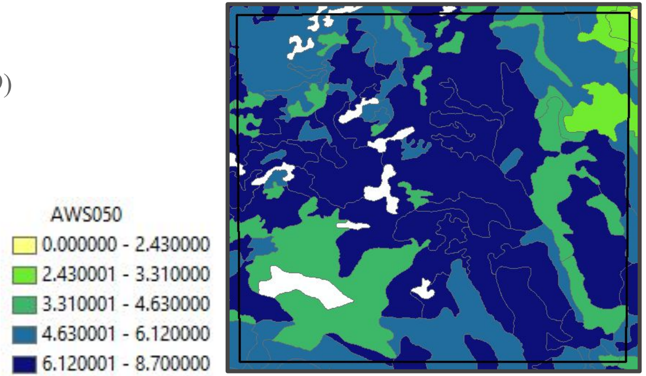


Variable Importance:

- From all tested models, height consistently an influential predictors.
- Elevation - Less influential (smaller gradient than Paz-Kagan et al. 2019)

Partial Dependence:

- Height - Taller trees had a higher mortality probability (agreed with Stovall et al. 2019)
- Rock cover - Deeper soils with greater water storage had a higher mortality probability (disagreed with Paz-Kagan et al. 2017, agreed with Stovall et al. 2019)
- Distance to streams - higher mortality further from streams (agreed with Paz-Kagan et al. 2017)
- Substrate - Most SDV variables correlated, all uninfluential



Bark beetle damage a likely source of model for remaining unexplained variance in tree mortality

Discussion:

Limitations

- Remote sensing data has information from trees at the top of the canopy
- No distinction between live trees and trees recently in the green-stage of mortality, right after an attack before needles begin to discolor
- Limited number of training/validation genus samples over a small spatial extent makes genus classifier precision difficult to assess
- Low model fit affect applies to variable importance and partial dependence plot results
- Bark Beetles:
    - Can't explicitly account for them. If cause of mortality is from beetles attacking trees weakened from drought, environmental factors are only an indirect cause of mortality

Discussion:

Future Work

- Gather more survey points throughout the image and perform a species classification
- Check trees for bark beetle damage and spatially assess model residuals, see if high residuals match up with location on the ground with lots of bark beetle damaged trees
- Study area affected by 2021 blue fire recently, 2020 creek fire nearby. Live/dead classification map with distinction between red-stage and gray-stage mortality trees could possibly be used to better model fire spread
- Need higher temporal resolution imagery from satellites.
- Need an integrative approach that includes climate, biotic factors and site-specific conditions that may enable us to predict future mortality patterns in response to drought conditions.

https://www.fresnobee.com/news/california/fires/article252487128.html

Conclusion

Areas with these environmental attributes may find:

- Shift in community composition over time
- Increased fire hazard risk
- Reduced biodiversity and resiliency
- Decrease in forest net primary productivity
- Reduced ecotourism

This study provided:

- A framework for detecting live and dead trees using publically available HSI and lidar data
- Finer-scale mapping of tree mortality over the study area than is provided by the USFS ADS
- More robust information that can inform stakeholders on what factors contribute to tree mortality to help monitor, manage, and conserve forests in a climate-informed manner

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