Monitoring Drought Induced Dieback in Oak Woodlands in the Santa Monica Mountains National Recreation Area

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PROJECT GOALS

The goal of this FPL intern project was to explore the best method to monitor oak dieback across the Santa Monica Mountains National Recreation Area. Unfortunately, there was not enough time to provide a comprehensive analysis of oak dieback patterns due to both fire and drought. Instead, I worked on a framework for long-term landscape scale oak monitoring since the first step in assessing trends in oak dieback is simply determining where dieback has occurred. My research this summer focused on drought dieback to answer the following questions:

- What is the best method to identify drought-induced oak dieback?
- Can the method distinguish between different severities of oak dieback?

BACKGROUND

The study period selected was from 2004-2020. During this period there was a 3-year drought from 2002-2004, an extremely intense, short-duration drought in 2007, and a 1200-year record mega drought from 2012-2018 (**Figure 1**). During these same decades, beginning in 2005, there were five major fires greater than 1000 ha, as well as several smaller fires that are of interest because of their timing during the drought cycle and the presence of oak woodlands (**Table 1**)

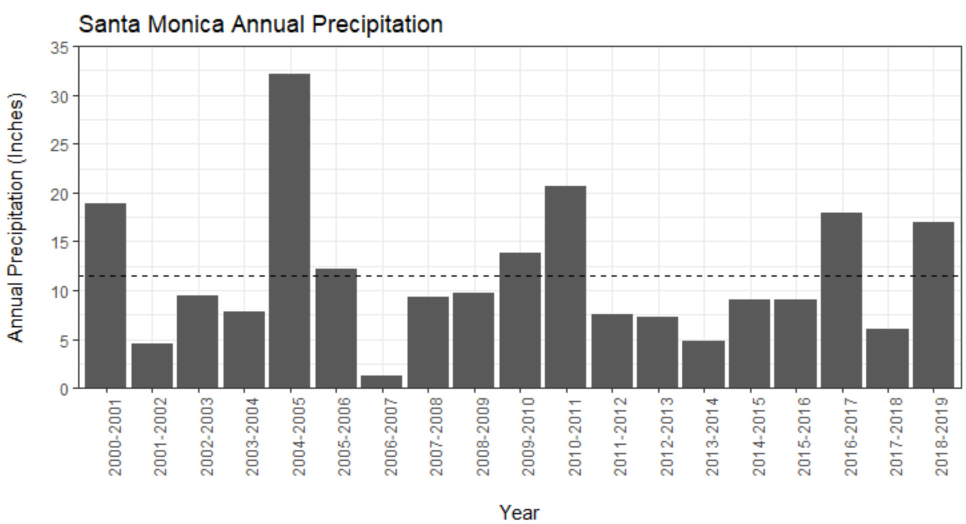


Figure 1: Annual precipitation for SAMO. Data from http://www.laalmanac.com/weather/we139a.php. Precipitation year = July 1 of one year to June 30 of the following year.

The dates of the mega drought vary in news reports and scientific literature. The U.S. Drought Monitor and many scientific papers refer to the start of the drought in 2011; the U.S. Drought Monitor declared the start of the drought on December 27, 2011.[1] Many scientific papers refer to the drought as the 2011-2016 drought, despite additional drought months after 2016. Governor Jerry Brown declared the drought over on April 7, 2017[2], however all of 2017 was still in a severe drought according to the Palmer Severity Drought Index (PDSI) (**Figure 2**). The U.S. Drought Monitor did not declare the drought over until May 5 2019.[1] For the purposes of this project, the drought was considered to last from 2011-mid 2018. Mid 2018 was chosen as the end date for the drought in SAMO despite several consecutive months of moist conditions because annual precipitation was still below normal and oak dieback in the park was very apparent in August 2018 Google Earth Imagery.

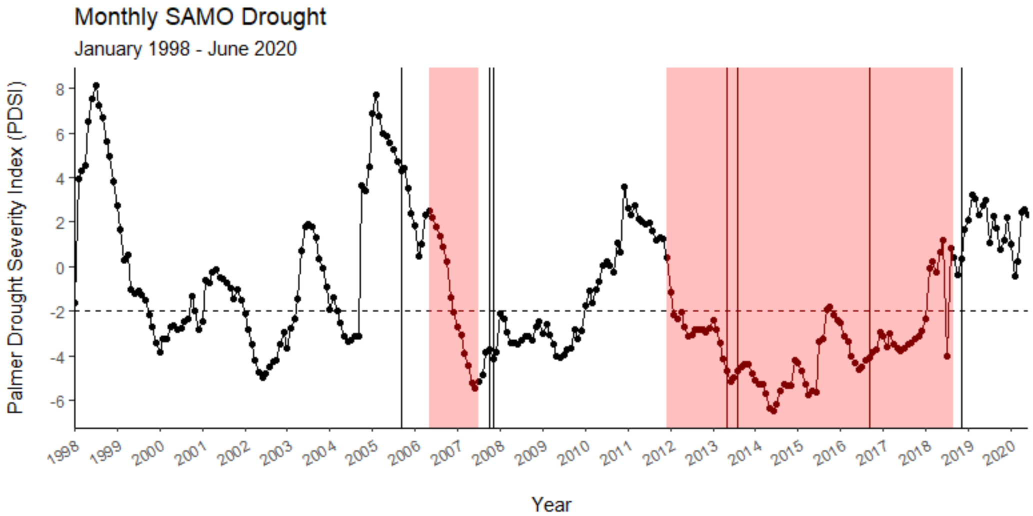


Figure 2: PDSI of SAMO. The red boxes indicate notable droughts. The left box is the short, yet severe 2007 drought in which there was record low precipitation (<2 inches). The right box is the California mega drought, from December 2011-October 2018. The vertical black lines indicate major fires after 2004 that affected several oak woodlands. From left to right is the Topanga Fire, the Canyon Fire, the Corral Fire, the Springs Fire, the 2013 Old Fire, the 2016 Old Fire, and the Woolsey Fire.

SAMO FIRE HISTORY IN OAK WOODLANDS

Oak woodlands have been mapped in SAMO as part of the 2007 Santa Monica Mountains National Recreation Area Vegetation Map, which was based on 2001 aerial photo imagery. According to this source, there are approximately 8,243.5 acres of oak woodlands in the park. However, the true acreage of oak woodland is lower since Google Earth revealed some oak boundaries contain other vegetation and a few do not contain any oaks.

Cal FRAP fire perimeters were used to assess the fire history of oak woodlands in the park from 1925 - 2018. The number of oak polygons burned in the major fires during the two decades of the study period is listed in **Table 1**.

Table 1: Number of oak polygons burned in each major fire that occurred after 2000.

Fire Name	Date	Num Affected Oak Polygons
Topanga	9/28/2005	174
Canyon	10/21/2007	20
Corral	11/2/2007	78
Springs	5/2/2013	179
Old Fire 2013	8/18/2013	13
Old Fire 2016	6/4/2016	21
Woolsey	11/8/2018	1156

270 fires have occurred within SAMO since the start of the fire record in 1925, burning a total of 491,686.5 acres (**Figure 3**). The number of oak stands and number of acres of oak woodlands burned by fire in this time frame is listed in **Table 2.** It is important to note the FRAP layers do not represent a complete fire record; it is incomplete for the late 1800s and early 1900s, but is mostly reliable after the 1950s.

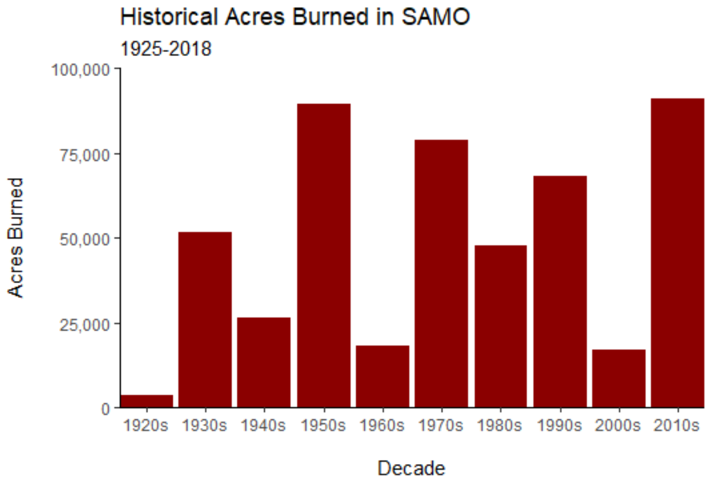


Figure 3: Number of acres burned per decade in SAMO from 1925 - 2018.

The oak woodlands have a heterogeneous fire history (**Figure 4, Table 2**). The average (and median) number of fires in each oak stand is 3, with the number of fires ranging from 0 to 10; 935 acres have not burned since the beginning of the fire record in 1925 (**Table 2**). From 2000-2018, the average number of fires per oak stand is 1.

Table 2: Number of oak polygons (noted by the "Count" column) and oak acres that have been burned once, twice, etc.

Number Historic Fires	Count	Acres Burned
0	167	935.43
1	218	1,000.73
2	420	1,615.78
3	488	1,709.70
4	371	1,377.48
5	246	858.14
6	203	589.03
7	34	88.59
8	27	61.29
9	5	6.26
10	1	1.07

A data frame and ArcGIS layer were created containing the fire history of the oaks (See oak_fire_history.csv/.shp, oak_fire_history2005.csv/.shp, oak_fire_history2005main.csv/.shp). They contain information such as the number of fires in each oak polygon, the year in which the fire burned, time since last fire, last fire to occur in each stand, and fire return intervals. The former file contains information on all fires that have occurred in SAMO, the second file contains information on only fires that have occurred from 2005-2018, and the latter file contains information only on fires that have occurred from 2005-2018 that affected more than 15 oak polygons, in addition to the 2013 Old Fire which affected 13 polygons.

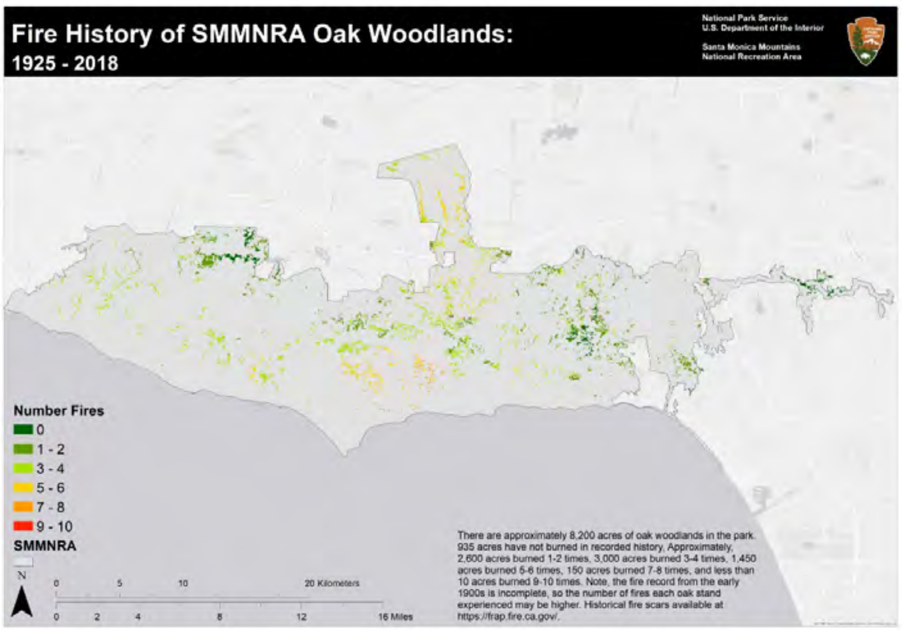


Figure 4: The number of fires that have occurred in each oak polygon in the fire history record. **A high-resolution version** of the map is available is in the "SAMO fire history map" folder.

METHODS

Satellite Imagery Review

To determine the best imagery to use to monitor drought, I assessed which satellite imagery was available, the resolution, the bands, and the years the imagery was available. My results are summarized in **Table 3**, but more detailed analysis can be found in Supplemental 1.

I assessed dozens of satellites ranging from very high resolution to very coarse resolution. When picking the imagery to use, I assessed 5 essential criteria:

1. Free
2. Easy to access
3. Currently available for use
4. Contains at a minimum red, green, blue, and near-infrared band
5. Imagery is annual imagery

An important, but not essential criteria, was that the imagery was available at a minimum a couple years before the drought (to provide pre-drought baseline data) and was available throughout the entirety of the drought plus one-year post drought (i.e., 2011-2019). Free imagery was essential because there was no significant budget available to purchase imagery. Easy to access was also an essential criteria because the internship was only 12 weeks, so I did not have time to wait to hear back for imagery requests. SAMO does have a good relationship with employees at the NASA Jet Propulsion Lab (e.g., Natasha Stavros), so future projects may be able to use those connections to get higher resolution imagery. RGB and NIR bands were essential because drought indices like NDVI (Normal Differenced Vegetation Index) and EVI (Enhanced Vegetation Index) require NIR. Having continued coverage from before, during, and after the drought was not essential because other researchers have circumvented this problem by combining imagery from other satellites to conduct long-term studies. However, I suspect this is feasible when the imagery is the same resolution and several satellite sources are available.

Most very high-resolution imagery is not free, so I was not able to use it in this analysis. The exception being Worldview 1-4 imagery which is free for government employees or government contractors but required submitting a form to gain access. I submitted one, but never heard back despite following up. However, this imagery should be explored for future use as it is available several years before the drought, during the entirety of the drought, there will be continued coverage after 2020. I suspect higher resolution imagery will be best for monitoring drought since larger pixels can capture more heterogenous vegetation, which makes the results less robust.

From **Table 3**, only Sentinel-2, Landsat, MODIS, and AVHRR imagery met the 5 essential criteria. MODIS and AVHRR were much too coarse for this analysis. Sentinel-2 was higher resolution (10-m) but was only available starting in 2015 with no other imagery available to provide pre-drought imagery. Ultimately, I chose to use 30-m Landsat imagery because it was the highest resolution imagery that met the 5 essential criteria: easy to access, free, available for use, contains R,G,B, and NIR bands, and is available annually. An extra bonus was that Landsat has been available almost monthly since the mid-1980s, which would allow for a long baseline average.

Table 3: Assessment of different criteria for some common satellites. A more in depth (but less organized) assessment is in Supplemental 1. The colors rank if a satellite has met a certain objective: Green = meets objective, Orange = somewhat meets objective or unsure, Red = did not meet objective.

Source	Resolution	Easy to Access?*	Free?*	Currently Available for use?*	R, G, B, NIR bands?*	Years available*	Continued Coverage?
Google Earth	15cm – 15m	Yes	Yes	Yes	No	2000s-current	Yes
Wolrdview1	0.5	Somewhat	Yes	No	No	2007-current?	Unsure
NAIP	1m	Yes	Yes	Yes	No[1]	Every 3-5 years	Yes
Lidar	1m	Yes	Yes	Somewhat[2]	No	2016 or 2018[3]	No
Worldview 2-4	1.5-2.4m	Somewhat	Yes	No	Yes	2009-current	Yes
Quickbird	2.6m	No	Unsure	No	Yes	2001-2014	No
Rapid Eye	5m	No	No	No	Yes	2009-2020	No
Sentinel-2	10-20m	Yes	Yes	Yes	Yes	2015-current	Yes
AVIRIS	15.6	Somewhat[4]	Unsure	Yes	Yes[5]	Unsure	Unsure
Landsat	30m	Yes	Yes	Yes	Yes	1980s-current	Yes
MODIS	500m	Yes	Yes	Yes	Yes	2000-current	Yes
AVHRR	1,000m	Yes	Yes	Yes	Yes	1979-current	Unsure

*: One of the five essential criteria

1: NAIP just has R, G, and B bands; no NIR
2: Lidar in the park is available and free but requires a lot of processing before being able to use it.
3: Lidar is only available in LA county in 2016 and only available in Ventura County in 2018. No overlap.
4: Previous SAMO NASA interns have used AVIRIS imagery (NASA 2017a, 2017b), but I was unsure of how and where the NASA team got their imagery. However, since it has already been used JPL contact Natasha Stavros should have access to it.

5: Unsure if AVIRIS comes with R, G, B, and NIR bands, but it is possible to calibrate AVIRIS spectral library to work with Landsat imagery which contains those bands.

Vegetation Index

I considered several approaches to monitor drought: enhanced vegetation index (EVI), normalized difference vegetation index (NDVI), normalized difference water index (NDWI), multiple endmember spectral mixture analysis (MESMA) green vegetation (GV) fractions, and water use efficiency (WUE) (Malone 2017). EVI, NDVI, and GV fractions essentially measure vegetation greenness; MESMA GV fractions are a more advanced approach to EVI and NDVI. NDWI measures water content of leaves and thus essentially is used to monitor drought stress of plants. WUE also measures drought stress. I ultimately selected EVI for my analysis for a combination of reasons:

- the 12-week project time constraint did not allow me to learn more advanced techniques such as MESMA and WUE.
- MESMA has already been used in the park to analyze the drought and oaks, so I did not want to redo that analysis. I thought a better use of my time would be to attempt a different approach that could be used in addition to the MESMA results or could be compared to the MESMA results.
- EVI is more robust than NDVI as it does not get saturated at higher levels. Additionally, the equation for EVI accounts for some atmospheric interferences while NDVI does not.
- EVI and NDWI are highly correlated (**Figure 5**), and NDWI did not show any distinctions between vegetation types (**Figures 6 and 7**) unlike EVI which had inter-annual variation. This monthly variation allowed me to distinguish between EVI trends for different vegetation types.
- I was interested in how a simple approach like EVI, which is a straightforward greenness index, compared to more advanced techniques. Future researchers can attempt a more advanced approach to detect and monitor drought, which can then be compared with my estimates of drought dieback. In addition, a simple approach would allow future NPS employees with basic R and ArcGIS experience to replicate my results for future drought monitoring or retroactive drought monitoring of other vegetation types like chaparral or riparian woodlands.

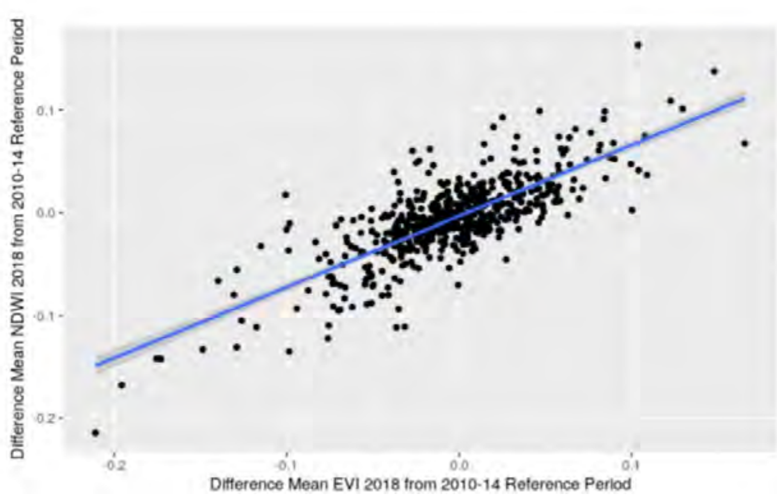


Figure 5: From students in Aaron Ramirez's class. See paper in Resources folder.

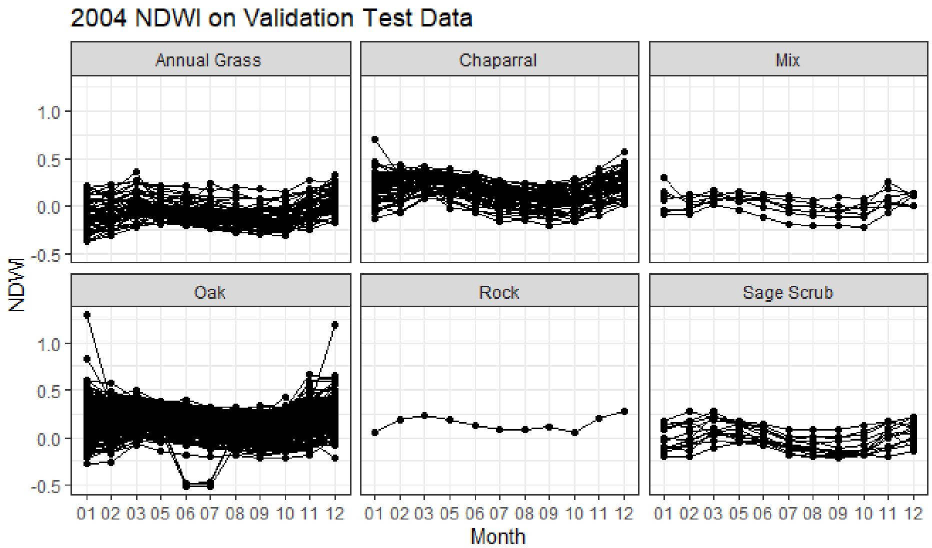


Figure 6: 2004 NDWI values for pixels dominated by different vegetation types. There is little change in NDWI during the year. Additionally, there is a lot of overlap in NDWI trends between the other vegetation types and the oaks which would make it difficult filter out non-oak dominated pixels (see Analysis).

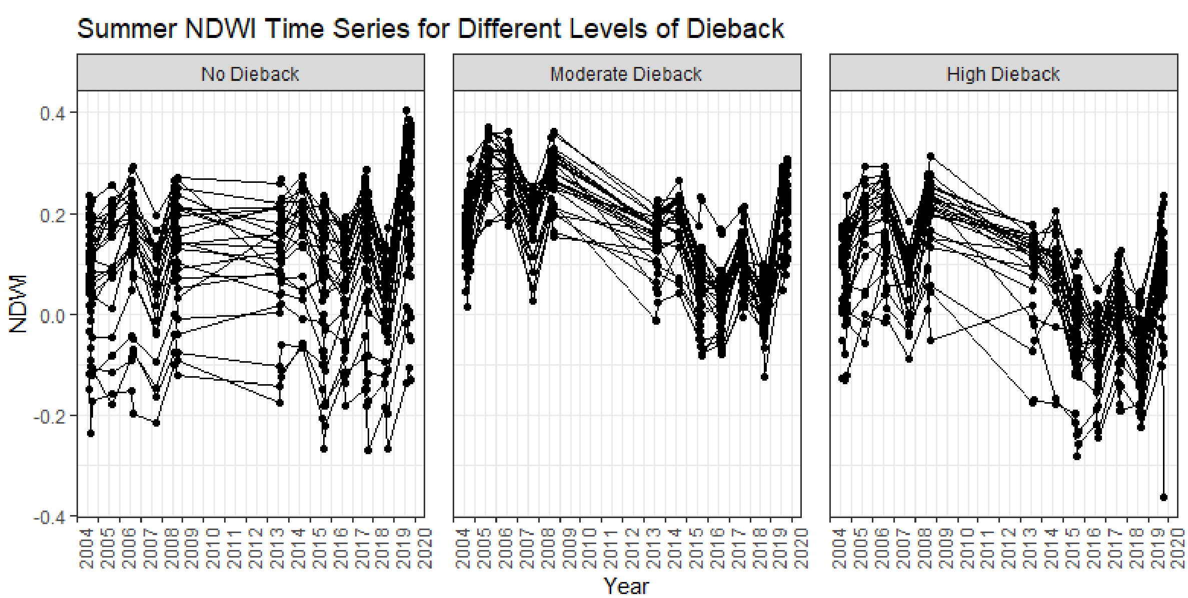


Figure 7: Summer (August, September, October) NDWI for oak pixels with different levels of dieback.

<u>How I got EVI</u>

- <u>Image selection:</u> I had to hand select images from [USGS Earth Explorer.](#) I got monthly images from 2004-2020. Some months either had no images available, had too many clouds over the study area, or the next available image in one month was taken too soon to the only available image in the previous month (I tried to avoid getting images < 2 weeks apart). 2012 Landsat imagery is available, however there was an error with the satellite, so there are several pixels in each image with NA values. While there are methods to overcome this issue, there was not enough time in the internship to learn and apply these corrections, so 2012 is skipped in my analysis.

- Rename files: I manually renamed files the USGS imagery was stored in to the name of the year and month the image was taken (e.g. 2004_09). An iterative R code could have done this in amore automated process, however the months of the available images were not consistent between years to apply such a code.
- EVI calculation: EVI = 2.5*((NIR – Red) / (NIR + 6 * Red – 7.5 * Blue + 1)).
  EVI was calculated in R using an iterator (see drought_indices.Rmd). The name of the file storing the USGS imagery was used to name the output EVI rasters. Each band was multiplied by 0.0001 to account for the scaling factor of Landsat images.
- Pixel values: In ArcGIS, EVI rasters were clipped to the extent of the oak polygons, then the Raster to Point tool was used to convert a raster to a shapefile with individual EVI values for each pixel in the oak woodland polygons. Raster to point can be done in R, but I wanted to make sure the unique number identifying each point was consistent between images and that was easier to do in ArcGIS. Additionally, ArcGIS had faster computational time than R for this step. The ModelBuilder model is available in the Toolbox in my files (see raster to point evi iterator). See Workflow and Documentation Final.doc for troubleshooting and how to use the model.
- Import shapefiles: The pixel values from each image were loaded into R using an iterator that reads in multiple shapefiles, uses the name of the shapefile (which is the year and month the image was taken) to add a new column to the data frame, and then combines all data frames for each image were into a single data frame (see raster to point conversions.Rmd).

Using Climate Engine is another method for getting EVI. This site provides indices like EVI, NDVI, and NDWI for Landsat and Sentinel-2 imagery. There are also other free satellites and indices available on this site. Users can select an average value for a custom date range (e.g., average EVI from August, September, and October) and a raster will be downloaded that averages EVI from those months into a single image. This site is a faster, more automated method for EVI that does not require manually calculating EVI and would reduce the number of images needed to download. For directions on how to uses this site see GIS_R Methods.doc in the Resources folder (the person who created this document was doing a different analysis, but the paper does a good job of showing how to use the tool). I would have used this method, but I did not know about it until after I had already processed all my imagery. I compared average summer EVI values for one year using Climate Engine data to my hand calculation of average summer EVI of the same year and got very similar results.

ANAYSIS: APPROACH TO ASSESSING DROUGHT

There are a couple approaches I could have taken to monitor drought using Landsat and EVI. Other papers have used classification algorithms (Liu et al. 2006, Kelly 2002, etc.) and there has been an increased use of machine learning or black box learning in recent literature. Some researchers used spectral enhancements and or topographic corrections to aid in classification (Kelly 2002). Some approaches by current researchers are far outside my skill and abilities, use methods that requires data I do not have access to, and would require far longer than 12 weeks to replicate (Meng et al. 2018, etc.). Due to the time constraints of the project I opted to go with a simple approach that did not require arduous corrections or advanced skills. Additionally, this simple approach will provide a good baseline for future work that uses more advanced or technical approaches to see how well a simple approach compares to a more complex one and if the extra steps and time are worth the effort.

Workflow method

My methods followed the workflow approach described below.

- Obtain monthly Landsat imagery from USGS Earth Explorer. Manually rename each file to the year and month the image was taken. This enabled me to save the image date as the name of future output rasters and shapefiles.
- Calculate EVI for each image in R (see drought_indices.Rmd).
- Use model in ModelBuilder in ArcGIS to clip the rasters to the oak polygons and convert values stored in raster cells to individual points (Raster to Point tool).
- Use a loop in R to import the raster to point shapefiles and store them into a single data frame (see raster to point conversions.Rmd)
- Convert some raster pixels and oak polygons to .kmz to use Google Earth imagery to identify pixels for test data (e.g., classify oak dieback, classify dominant vegetation within a pixel). I always had to select sub-sample of pixels because Google Earth would freeze with too many pixels. I quickly realized this created issues if all the selected sub-sample of pixels were in the same area as the EVI trends observed in those samples were not representative of the entire study area. So, it is best to use a code to randomly select pixels for test data.
- Explore the trends in the test data (made pretty graphs).
- Determine pixel removal threshold, which was done subjectively due to time constraints.
- Calculate annual EVI Z score
- Determine a dieback threshold using a binomial logistic regression
- Putting it all together to assess dieback in all oaks across the landscape
    - Remove pixels that were unburned from 2005-2016
    - Apply the pixel removal thresholds
    - Calculate EVI Z score for 2016
    - Apply the dieback thresholds
    - Calculate acres suspected of high dieback and no dieback

Pixel Removal Threshold

This step was added to the analysis when it was discovered that many pixels had very low EVI values, which was due to pixels inside oak polygons being dominated by vegetation other than oaks (usually annual grass, urban structures like roads or houses, sage scrub). Removing these pixels by hand was too time consuming, so applying a quantitative threshold was the most time efficient approach. While no perfect threshold was available, it increased the robustness of our results knowing that we were primarily analyzing trends in oak dominated pixels, not other vegetation types.

The 2007 vegetation layer was used to identify oak woodlands in SAMO. I used *Quercus agrifolia* and *Quercus lobata* vegetation types. 2,180 polygons (36,075 pixels) were identified which covered 8,243.5 acres. I used 2004 imagery, particularly September 2004, for my initial assessment of trends in oaks and other vegetation types. 2004 was used because it was the year before the 2005 Topanga Fire and September is generally considered a good month to use. At the end of summer understory annual vegetation and sub-shrubs have finished senescing and will have less effect on remote sensing indices, particularly indices that measure greenness. September imagery is also the preferred month of a fellow remote sensing colleague (Kibler 2019).

Initial assessment of oaks and drought looked at the average EVI of oak polygons. However, this approach was quickly dismissed in favor of looking at EVI of individual oak pixels. Oak polygons often contained other vegetation inside the polygon, such as annual grass, urban structures, or sage scrub which have lower EVI values than oaks and thus would lower the average EVI value and give an incorrect view of what is actually happening to the oaks.

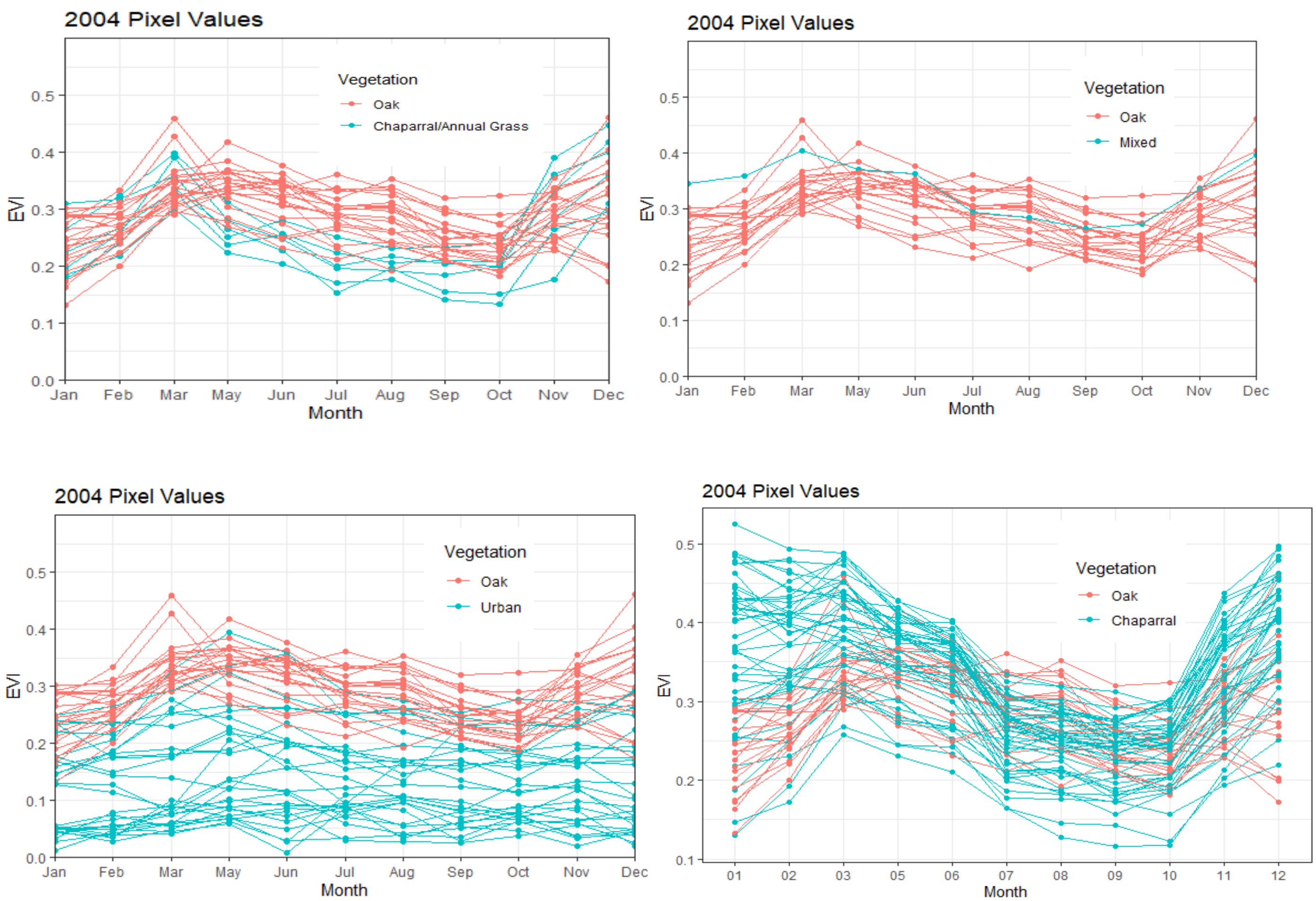


Figure 8: Monthly EVI values of initial sample data for pixels dominated by different vegetation types. The bottom right graph shows some clear trends between chaparral and oak EVI in January. However, this was the result of using sampled pixels selected from the same area. When using randomly selected pixels from across the park, this January EVI trend is no long evident (Figure 10).

Looking at individual pixels also had problems as well. Some pixels still had very low EVI values due to some pixels being dominated by annual grasses, urban structures, bare ground, or sage scrub (**Figure 8 and 9**). Unfortunately, chaparral dominated pixels had an EVI response very similar to oaks and pixels that contained a mix of oak or chaparral with lower EVI vegetation like annual grass, sage scrub, or urban areas also had an EVI response similar to oaks (**Figure 8 and 9**). Inexplicably, some oak dominated pixels had low EVI. In some cases, this could be attributed to clouds, shadows cast on the pixel by hillsides (due to the time of day the imagery was taken), but usually it was inexplicable; possibly it was due to atmospheric particles. Pixels not dominated by oaks had to be removed to ensure confidence that any assessment of dieback was actually dieback of oaks and not other vegetation types. Unfortunately, due to the overlapping EVI of oaks with some other vegetation types, this required also removing some oak pixels.

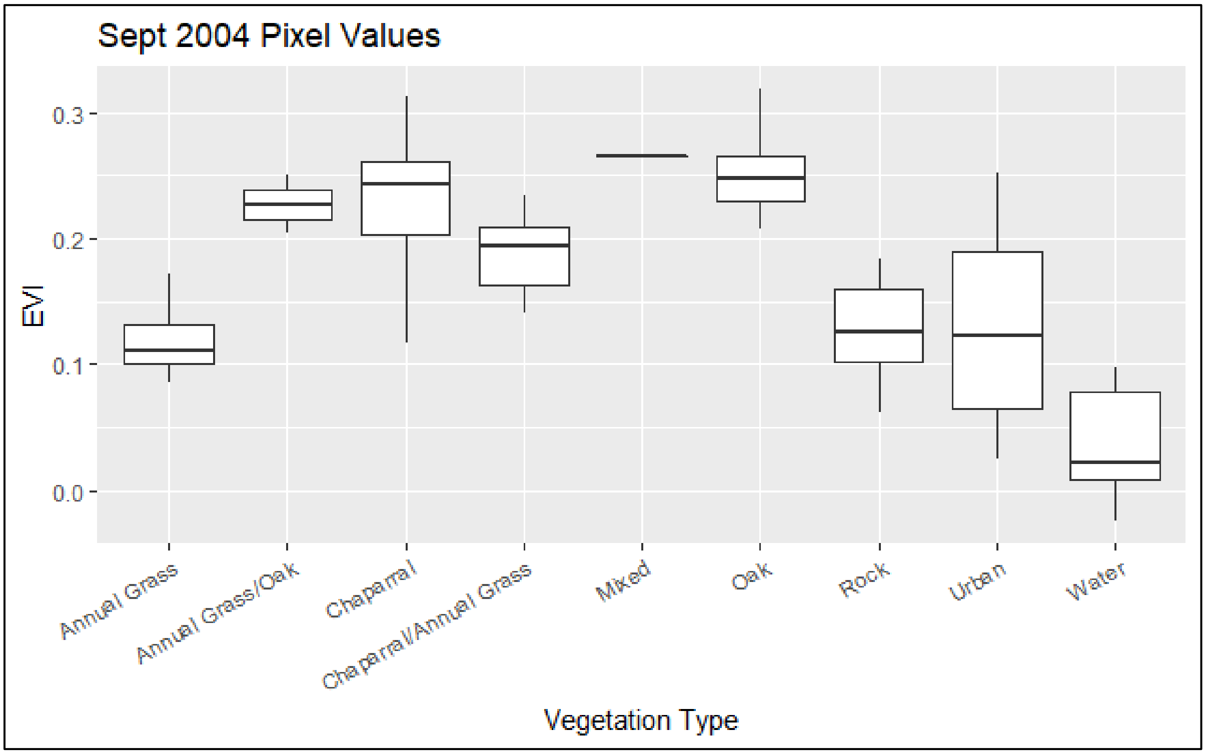


Figure 9: Range of EVI values for September 2004 for different vegetation types.

By looking at the graphs in **Figure 8 and 9**, I subjectively chose some quantitative thresholds to start removing non-oak dominated pixels. I considered an oak dominated pixel to contain greater than or equal to 50% oak cover. I classified the vegetation in 360 randomly selected pixels, which is 1% of the total number of pixels. The test data is available in validation_sample_results.csv (metadata also available). Note that the assessment of vegetation cover being >50% was subjective. In some cases, it was very clear what the dominate vegetation was and, in some cases, when there was closer to a 50:50 split, I used my best judgement; someone else could possibly classify cover differently. I then made some graphs to visualize the data spread (**Figure 10**), tested several thresholds, and classified the accuracy and misclassification of those thresholds (**Table 4**).

By comparing the range of EVI values for oak and chaparral in **Figure 10**, there was no longer a clear distinction in January EVI, so that was no longer considered a viable threshold. This showed the importance of using randomly selected data from across the study area instead of data from one location (which is the source of the data in **Figure 8**). It is not clear why some oak pixels have such low EVI in January; there could have been a shadow or cloud over the pixel, or they were affected by the mini drought in 2001-2003.

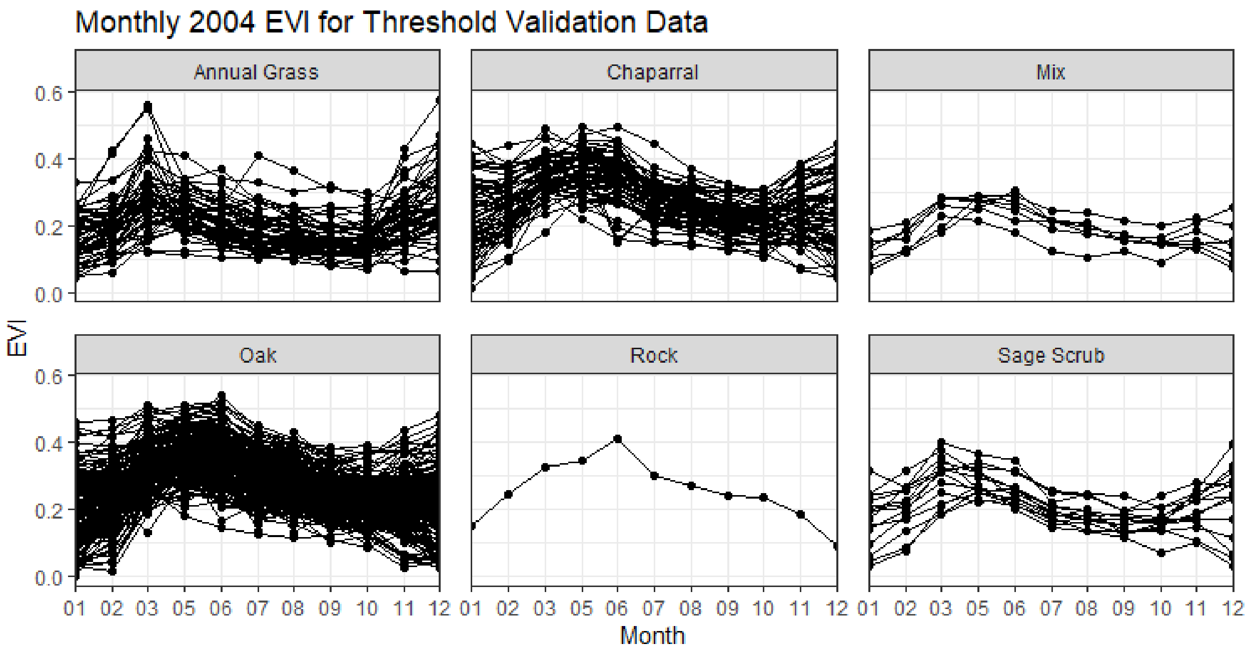


Figure 10: monthly EVI of 360 randomly selected pixels to validate vegetation type thresholds. By comparing the range of EVI values for oak and chaparral, there is no longer a clear distinction in January EVI.

Table 4: Accuracy results of the pixel removal threshold. Oak classification accuracy and the misclassification of other vegetation as oaks were both used to assess the best threshold. Threshold hold test = test number and threshold value. For example, 1;sept < 0.18 was test 1 in which all pixels with September 2004 EVI < 0.18 were removed; this was a one-step threshold. 5; sept <0.18 delta1 > 0.2 is test 5 in which all pixels with September 2004 EVI < 0.18 were removed and then pixels with a decrease in March and October EVI > 0.2 were also removed. Oak pixels = number of oak pixels out of 209 that were correctly classified as oaks. Accuracy Oak = Oak Pixels/209. Other Veg Pixels = number of pixels with < 50% oak incorrectly (out of 151) classified as oaks. Misclassification Other = Other Veg Pixels/151.

Threshold Test	Oak Pixels	Other Veg Pixels	Accuracy Oak	Misclassification Other
1; sept < 0.18	185	78	0.885	0.517
2; sept < 0.185	180	73	0.861	0.483
3; sept < 0.19	172	70	0.823	0.464
4; sept < 0.2	153	58	0.732	0.384
5; sept < 0.18 delta1 > 0.2	180	74	0.861	0.490
6; sept < 0.18 delta1 > 0.255	184	77	0.880	0.510
7; sept < 0.18 delta2 > 0.13	181	65	0.866	0.430
8; sept < 0.18 delta2 > 0.115	177	59	0.847	0.391
9; sept < 0.18 delta2 > 0.125	180	62	0.861	0.411
10; sept < 0.18 delta2 > 0.12	178	61	0.852	0.404

A one-step threshold, in which just pixels below a specified value in September 2004 (<0.18, <0.185, <0.19, and <0.2 EVI) were removed, resulted in high oak classification accuracy, but also high misclassification of other vegetation as oaks, which is undesirable. Most of the misclassified pixels were dominated by chaparral. September < 0.18 was chosen as the threshold for step 1 because it had the highest classification accuracy for oak pixels.

Applying a two-step threshold (**Figure 11**) resulted in the best classification accuracy and lowest misclassification rates. The second threshold was applied after the first threshold removed pixels with September EVI <0.18 and took advantage of the natural change in EVI for different vegetation types over the year. The first approach looked at the decrease in EVI in May (a peak) and October (a valley) (**Figure 12a**). The second approach looked at the rapid increase in EVI between October and December (**Figure 12b**), which is likely due to annuals like annual grass quickly taking advantage of rainfall. The second approach had the best distinction between vegetation and resulted in the removal of several pixels with other vegetation and only a few oak dominated pixels.

There is a trade off with high oak classification accuracy and decreasing other vegetation types misclassification. I selected threshold 8 (**Table 4**) which removed pixels with September 2004 EVI values < 0.18 and then removed remaining pixels that had an increase in EVI between October and December > 0.115. This minimized vegetation misclassification to 39.1% and only marginally reduced oak accuracy from 88.0% to 84.7%. The 84.7% accuracy was better than the MESMA approach by previous NASA interns in which MESMA was used to classify oak dominated pixels across SAMO (NASA 2017a, 2017b).

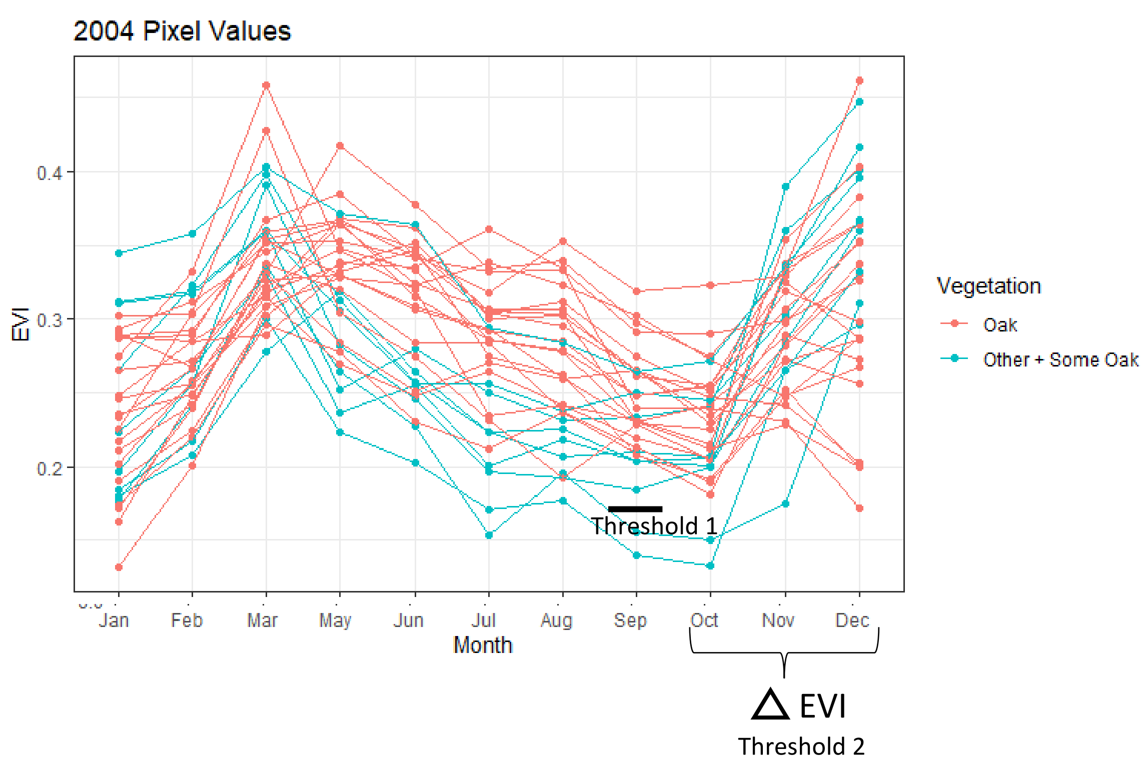
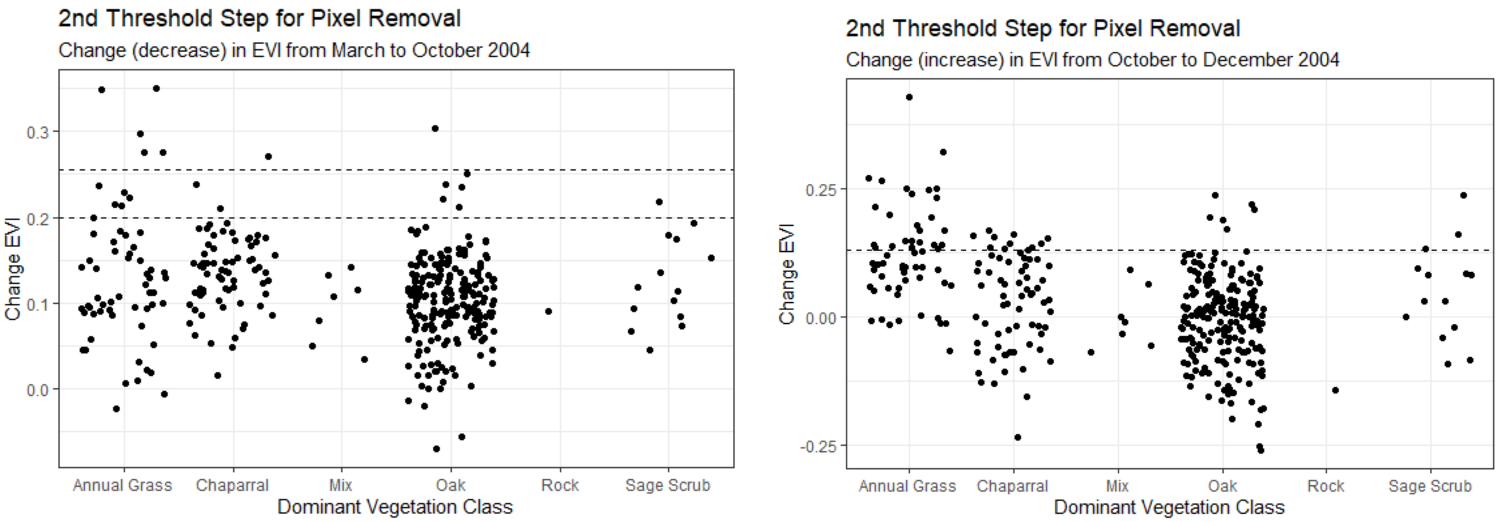


Figure 11: Visual representation of the 2 thresholds. Oaks, in pink, are oak dominated pixels (>50% of the pixel is covered with oaks).Other + Some Oak, in blue, are pixels dominated by other vegetation but contain some oaks (<50%).



a. **b.**

Figure 12: Shows how many pixels in the remaining test data, after removing pixels with 2004 September EVI <0.18, would be removed for different threshold values (dashed line). More non-oak dominated pixels would be removed using the increase in EVI between October and December (**b**), than the decrease in EVI between May and October (**a**).

<u>EVI Z score</u>

The EVI Z score was a way to compare EVI values during the drought to a pre-drought baseline (**Figure 13**). This enabled the comparison of pixels with different EVI values. This idea was from Edward Zhu who studied drought response of *Pseudotsuga macrocarpa* during the same mega drought working with Aaron Ramirez (Zhu 2018, available in Resources folder); other employees may know Aaron Ramirez who did part of his PhD thesis work in SAMO. EVI Z score can be calculated by hand picking imagery from USGS Earth Explorer or using imagery from Climate Engine. Edward used the latter and I used the former because I did not know of this website until much later in the internship. See Z_score_calculation.Rmd for how to calculate EVI Z score.

Three NASA DEVELOP projects previously studied drought and climate impacts on vegetation in SAMO (NASA 2017a, 2017b, 2019). They used the difference between years to assess dieback, e.g. 2014 – 2013, 2015 – 2014 (NASA 2017a). I believe this was because their AVIRIS imagery was only available starting in 2011 or a year or two into the drought, so they did not have or use pre-drought data. I did not try to replicate this approach using EVI because I wanted to use a pre-drought baseline as I thought would be more representative of true drought stress. However, it would be interesting to use a modified version of my approach by using summer EVI (average August, September, October) and calculating the difference between years like the NASA DEVELOP group to compare results. Due to time limitations I was not able to carry out this comparison, but it would have indicated if a more advanced approach of using MESMA and GV fractions was worth the extra effort and resources to monitor drought compared to a more simplistic approach of using easy to use Landsat imagery and EVI.

$$z = \frac{EVI\ year - EVI\ baseline}{\sigma\ \mathrm{baseline}}$$

Figure 13: EVI year = average summer EVI during a drought year (2011, 2013, 2014, etc.). EVI baseline = average summer EVI during a pre-drought period. Standard deviation baseline is the standard deviation of the baseline summer EVIs.

Edward Zhu used 1984-2000 for his baseline period. I used 2000-2004 because I was running low on time and calculating the extra years of EVI values was not possible. This period was one of short, moderate episodes of both drought and above average rainfall and fairly represents average variability in available soil moisture as measured by the PDSI (**Figure 2**).

Edward Zhu used June, July, and August as his "summer" EVI. I do not necessarily agree with this approach since his study area was much higher in elevation than SAMO, so annual vegetation and sub-shrubs could still be green in June and even July. I used August, September, and October to ensure minimal greenness in other vegetation types because most annual vegetation and subshrubs are senesced by August and there is unlikely to be significant rainfall by mid-October.

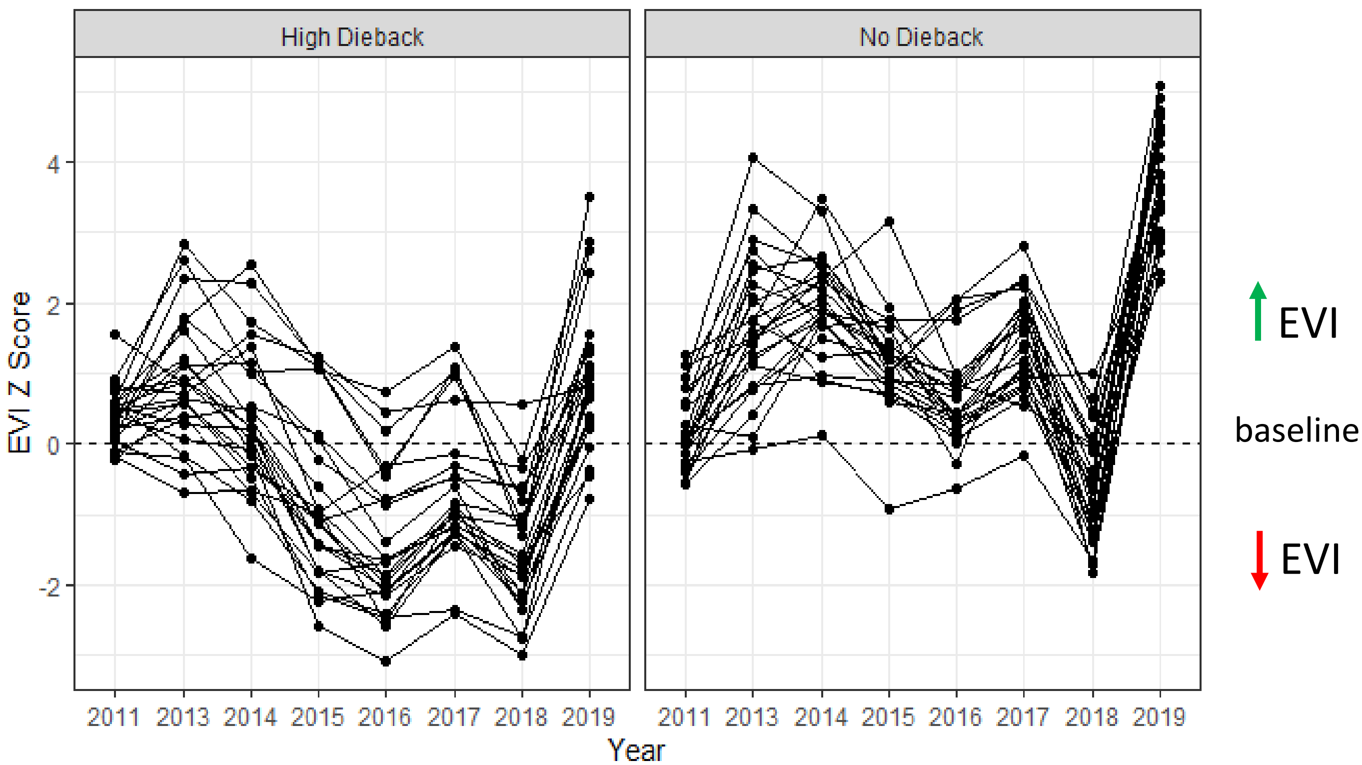


Figure 14: Trends of EVI Z scores for pixels classified as having high or no dieback. The dashed line at 0 is the baseline value. Values above 0 represent an increase in EVI compared to baseline, and values less than 0 represent a decrease in EVI compared to baseline.

<u>Dieback Threshold</u>

The final step in the approach was to determine how to classify dieback using the EVI Z scores. I used a threshold from a binomial logistic regression to provide a quantitative threshold value that could be applied to all pixels in the park and could potentially be used for quantifying dieback in future droughts. The model also provides different levels of confidence in the probability of dieback, as discussed below.

I originally classified 75 pixels as no dieback, moderate dieback, or high dieback. After looking at the EVI Z score of pixels for each group, I realized my classification of "moderate" dieback was ambiguous and I used a binary classification of high dieback or no dieback for all subsequent work as described below. There is further discussion of classifying moderate dieback in the RESULTS section.

After applying the two-step pixel removal threshold, an objective threshold was created to classify oak dominated pixels as having high dieback or no dieback. I used logistic regression and model selection with an information theoretic approach to 1) determine the best year to use EVI to classify dieback and 2) select a dieback threshold. I compared models relating presence or absence of dieback to EVI for seven years prior to and including the year dieback was manually assessed from Google Earth imagery (2011-2018) using AICc, judging the most parsimonious model to be the model with the lowest AICc.

The test data were small, n= 25 for high dieback and n = 25 for no dieback, due to time constraints. It would be best for the next person to follow the above steps and increase the sample size for this analysis. Test data are available in evi_pixel_dieback_verification_data.csv (meta data also available). 2018 Google Earth imagery was used to subjectively classify dieback. A further improvement on my approach would be to quantitatively classify dieback into several levels of dieback or into three levels of dieback: none, moderate, and high.

The question I answered with the model was: **In which year does greenness/EVI Z scores best predict oak canopy dieback?**

It was determined that most EVI Z scores values from 2011- 2018 were highly correlated with each other, thus the binomial model was run with EVI Z scores values from one year at a time. Model AICc values and relative weights were considered when selecting which year had EVI values that were most correlated with dieback (**Table 5**). The model using 2016 EVI Z scores best predicted canopy dieback.

Next, new models were created to explore the relationship with 2016 EVI Z values and dieback. Was the relationship linear or a polynomial? Four different models were run:

- Linear: glm(db ~ x2016, data=threshold_df, family="binomial")
- Quadratic: glm(db ~ poly(x2016,2), data=threshold_df, family="binomial")
- Cubic: glm(db ~ poly(x2016,3), data=threshold_df, family="binomial")
- Fourth-order: glm(db ~ poly(x2016,4), data=threshold_df, family="binomial")

The model with the best fit shows that 2016 EVI Z scores have a linear relationship with dieback (**Table 6**).

Next, we plotted the probability of the relationship between probability of dieback and 2016 EVI Z score. The curve of the probabilities is in **Figure 15a**, which was compared to a boosted regression tree (BRT) curve also plotting the predictions of dieback using 2016 EVI Z scores (**Figure 15b**). While the BRTs were not used to select a threshold, the BRT graph was used to validate the results of the binomial model which is supported by the similar shape of the two graphs.

Finally, different probabilities of dieback were chosen to determine a threshold value that can be applied to classify dieback across the landscape (**Table 8**). The thresholds are chosen by going to the mock test data which now contains the probability of dieback, selecting a probability of dieback (e.g., 95%, 90%, 65% etc.), and then using the EVI Z score value of the pixel closest to the selected probability as a quantitative threshold to classify dieback. The classification accuracy of the of the different thresholds plateaus after the 75% probability level (**Table 8**) due to the small sample size, another indication that a larger test data set is needed. The EVI Z score corresponding to a 75% probability of dieback is shown with a dotted line on **Figure 15**. See Dieback Threshold Analysis.Rmd for the code.

Table 5: Model outputs of the binomial models.

	Intercept	2011	2013	2014	2015	2016	2017	2018	df	logLik	AICc	delta AICc	Weight
mod2016	0.0238	NA	NA	NA	NA	-3.085	NA	NA	2	-11.1108	26.4769	0.0000	8.578617e-01
mod2017	1.3922	NA	NA	NA	NA	NA	-2.305	NA	2	-12.9378	30.1310	3.6540	1.380239e-01
mod2015	0.9515	NA	NA	NA	-1.8751	NA	NA	NA	2	-16.5626	37.3805	10.9036	3.679057e-03
mod2014	2.3646	NA	NA	-1.8188	NA	NA	NA	NA	2	-18.7022	41.6598	15.1829	4.330131e-04
mod2018	-1.6233	NA	NA	NA	NA	NA	NA	-1.8316	2	-23.9786	52.2124	25.7355	2.213211e-06
mod2013	1.5779	NA	-1.2091	NA	NA	NA	NA	NA	2	-27.2574	58.7701	32.2932	8.337534e-08
mod2011	0.2705	-0.6985	NA	NA	NA	NA	NA	NA	2	-34.0109	72.2770	45.8001	9.728694e-11

Table 6: Model outputs exploring the best relationship with 2016 EVI Z scores and dieback.

	Intercept	2016	2016^2	2016^3	2016^4	df	logLik	AICc	delta AICc	Weight
mod1	2.38000e-02	-3.085	NA	NA	NA	2	-11.1108	26.4769	0.0000	6.377347e-01
mod2	-3.61000e-02	NA	+	NA	NA	3	-10.9737	28.4692	1.9922	2.355223e-01
mod3	6.58400e-01	NA	NA	+	NA	4	-10.4098	29.7085	3.2315	1.267430e-01
mod4	-5.40432e+14	NA	NA	NA	+	5	-180.2183	371.8002	345.3232	6.586459e-76

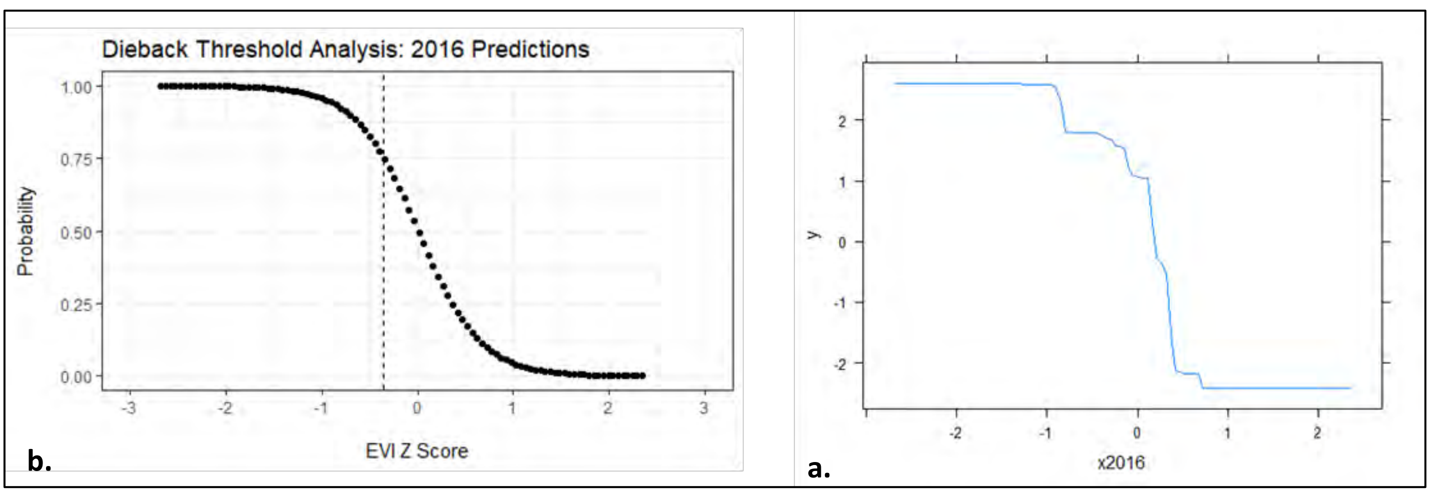


Figure 15: (**a**) Shows the dieback predictions for the mock test data of 2016 EVI Z scores. X axis = EVI Z score value and Y axis = probability of dieback. EVI z score at the dotted line corresponds to a 75% probability of dieback. (**b**) Is an output of 2016 EVI Z scores from a boosted regression tree.

Applying the Dieback Threshold at the Landscape Scale

See Landscape Dieback Assessment.Rmd for the code. This section applied all of the work in the approach section to assess dieback across all oak pixels in the park.

*Step 1 – Remove pixels that burned from 2005 - November 2016***:** Unburned pixels were targeted because 1) burned pixels would have had a low EVI Z score going into the drought and 2) the baseline used to calculate EVI Z scores is 2000-2004 (prefire years) but oak pixels with high burn severity can surpass baseline EVI values because of abundant understory growth affecting the remote sensing signal (Kibler 2019). Oaks burned in fires after 2016, including the 2018 Woolsey Fire, were retained because 2016 EVI Z scores were used to classify dieback, so pixels that burned after 2016 would not be incorrectly classified as having dieback. Finally, I used November 2016 as the cutoff date for analysis because only summer EVI values were used to calculate the annual EVI (August, September, and October). There are 36,075 pixels in the oak woodland polygons. Removing burned pixels from 2005 – November 2016 removed 6,873 (19.1%) pixels; 29,202 pixels remained.

*Step 2 – Remove non-oak dominated pixels***:** Apply the two-step pixel removal threshold. 8,973 (30.8%) remaining pixels were removed. 20,229 pixels (4,4498.7 acres) remaining to be assessed for dieback. The first step of the threshold removed 6,851 (23.5%) of the remaining pixels and the second step of the threshold removed 2,122 (7.3%) of the remaining pixels.

Step 3 – Calculate EVI Z scores for 20,299 pixels (4,4498.7 acres) of oak woodlands.

Step 4 – Apply the dieback threshold: A variety of thresholds were applied. Results are in **Table 8** and **Figure 16**.

RESULTS

Landscape scale dieback assessment

Of the total number of pixels (36,075) mapped as oak vegetation types from the 2007 SMMNRA Vegetation map there were 56% of the total remaining for landscape scale dieback analysis after burned (2005-2012) and mixed vegetation types were removed (**Table 7**).

Table 7. Percentage of pixels mapped as oak polygons remaining for dieback analysis after stratification for fire and non-oak dominated, mixed vegetation types.

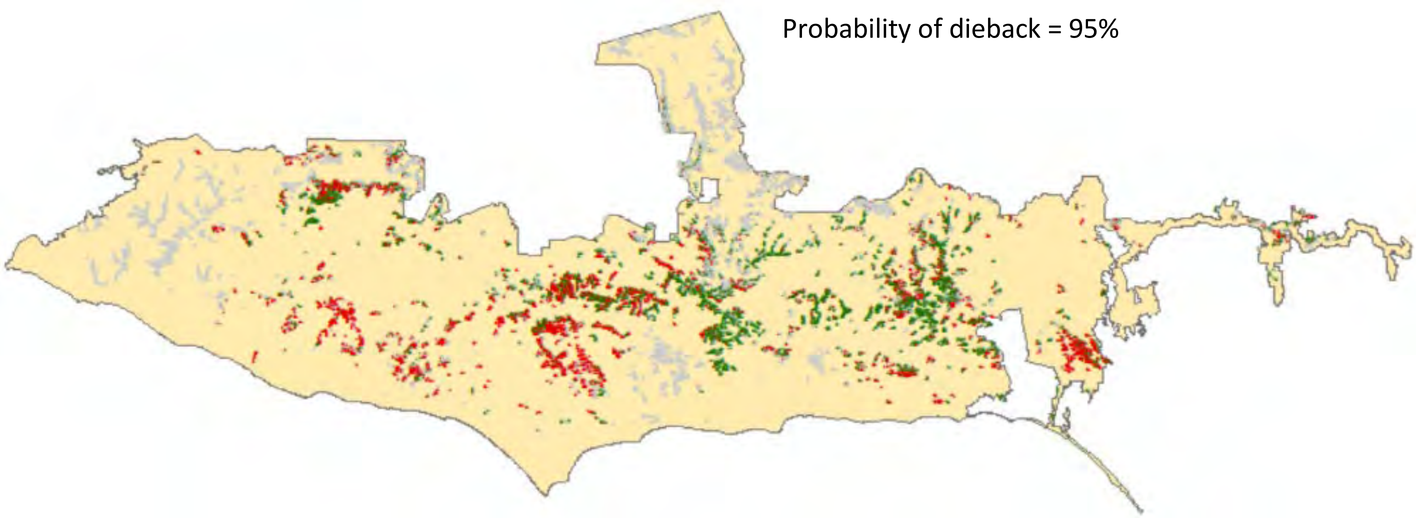
# Pixels	Stratification	Remaining #	Remaining %
36,075	Oak woodland polygons	36,075	100%
6,873	Remove burned 2005-2016	29,202	81%
6,851	Remove non-oak dominated -step 1	22,351	62%
2,122	Remove non-oak dominated -step 2	20,229	56%
	Total # available for dieback analysis	**20,229**	**56%**

EVI Z score thresholds were determined for classifying dieback using different levels of confidence in the probability of dieback (**Figure 15**) and then the number of acres of oaks classified as having high dieback or no dieback were calculated (**Table 8**). Accuracy plateaus after 75% due to the small sample size. A larger training sample size would provide better accuracy estimates. Note that as the probability of dieback decreases, more acres are assumed to have high dieback.

Table 8: EVI threshold values for different levels of confidence in probability of dieback. Acres of oaks classified as having high dieback or no dieback were then calculated. Accuracy plateaus after 75% due to the small sample size. A larger training sample size would be better.

Probability %	Threshold EVI Z Value	Dieback accuracy	No dieback accuracy	Acres classified as high dieback	Acres classified as not no dieback
95%	-0.947	68%	100%	2,053	2,445
90%	-0.705	76%	96%	2,464	2,034
85%	-0.555	80%	96%	2,704	1,795
80%	-0.444	80%	96%	2,866	1,633
75%	-0.353	84%	96%	3,000	1,499
70%	-0.268	84%	96%	3,128	1,370
65%	-0.197	84%	96%	3,223	1,276
60%	-0.127	84%	96%	3,310	1,188
55%	-0.061	84%	96%	3,394	1,105
50%	0.004	84%	96%	3,466	1,032

Maps showing the distribution of pixels with no dieback and high dieback across the landscape of the SMNRA for dieback probabilities of 95%, 85%, 75%, 65%, and 55% are mapped in **Figure 16**. Three time series visual inspection of pixels between 2012-2018 with a 55% probability of having high dieback are shown in **Figures 17a-c**. In retrospect, locations with a 95% probability of dieback should have been selected to better assess the dieback classification. Time constraints restricted my ability assess the accuracy of the model. Thus, future continuations should take this step.



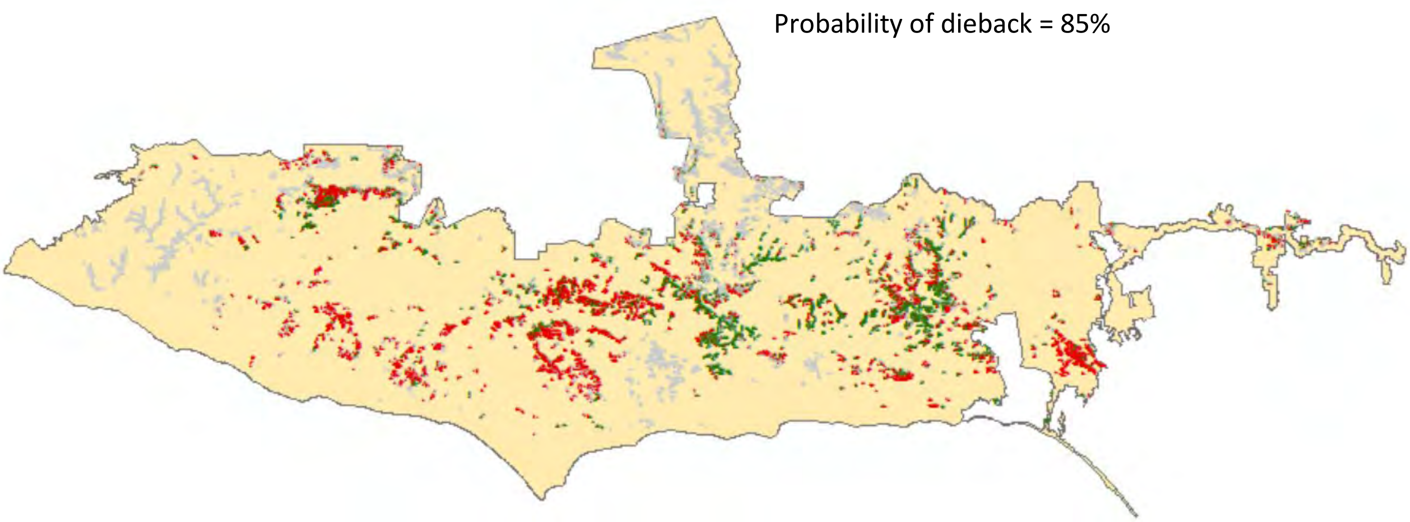


Figure 16: Visualization of dieback across all pixels qualified for analysis (i.e. after burned pixels and non-oak dominated pixels were removed). The different thresholds with different levels of confidence were applied. Red = pixels with high dieback, green = pixels with no dieback, and grey = removed pixels. Note: the maps at this scale may be a little misleading since there are many pixels being plotted, so some may be hidden.

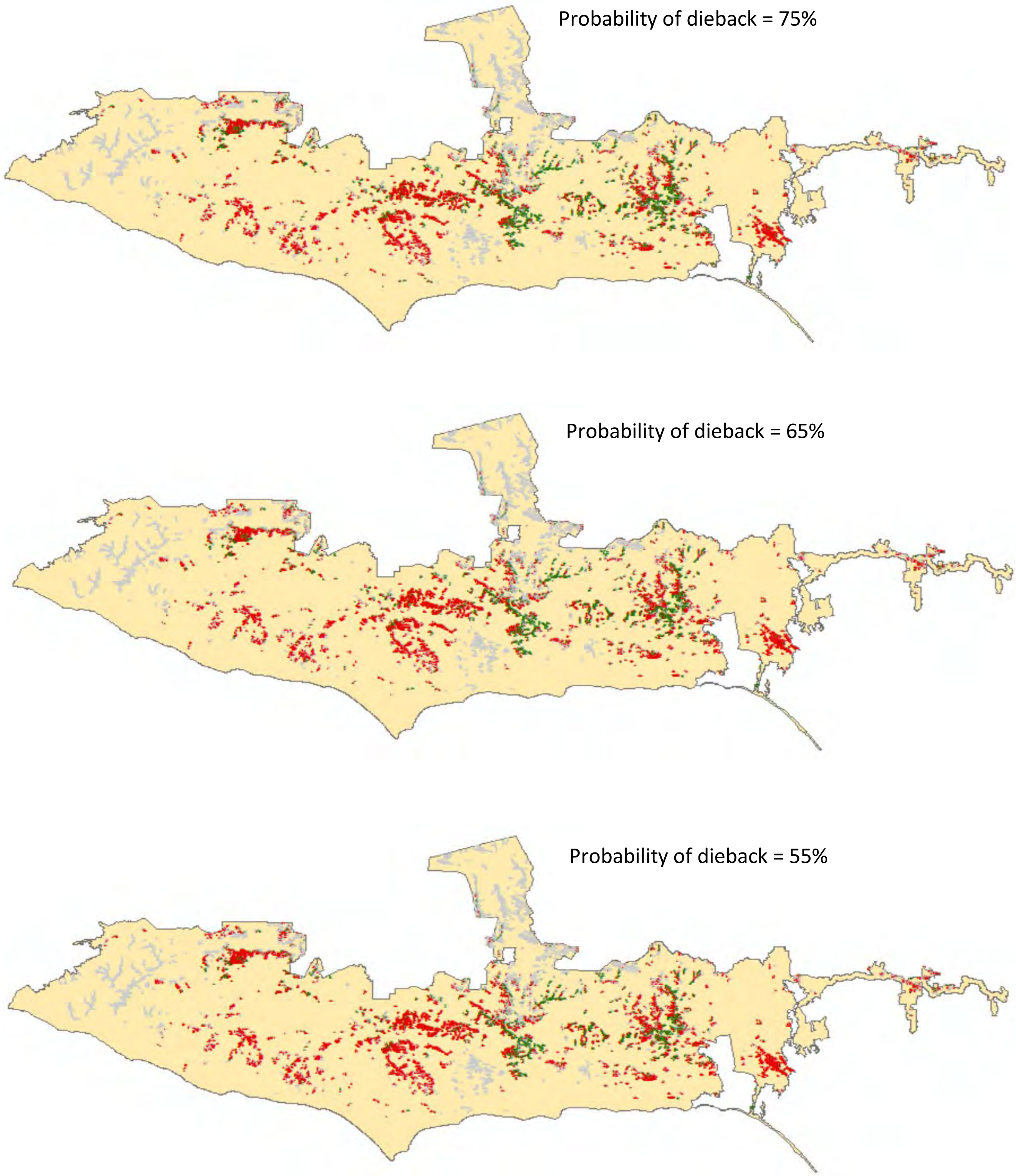


Figure 16 (continued): Visualization of dieback across all pixels qualified for analysis (i.e. after burned pixels and non-oak dominated pixels were removed). The different thresholds with different levels of confidence were applied. Red = pixels with high dieback, green = pixels with no dieback, and grey = removed pixels. Note: the maps at this scale may be a little misleading since there are many pixels being plotted, so some may be hidden.

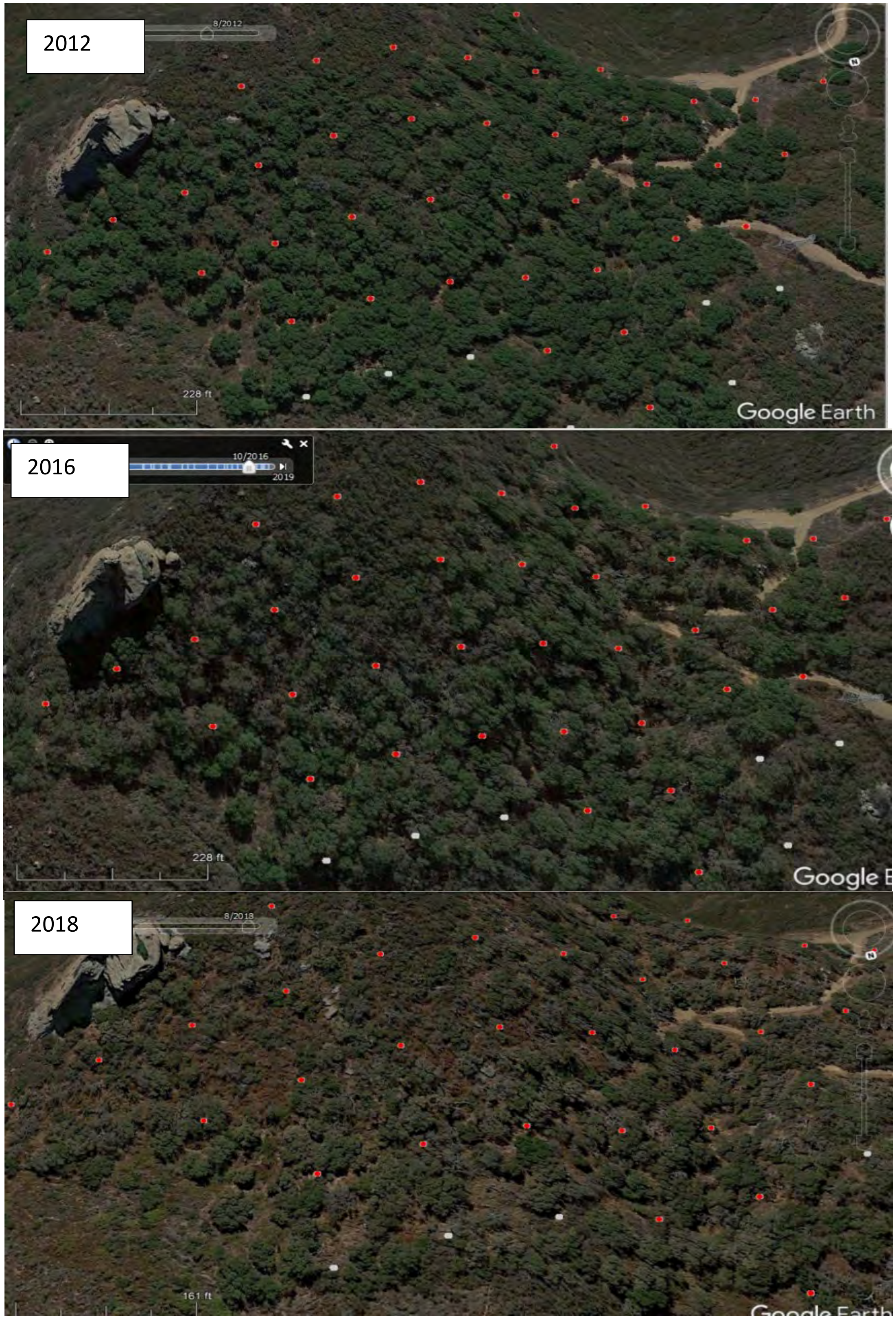


Figure 17a: 2012-2018 time series for visual inspection of pixels with 55% probability of having high dieback. Pixels with 95% probability of dieback would have provided a more graphic example of dieback

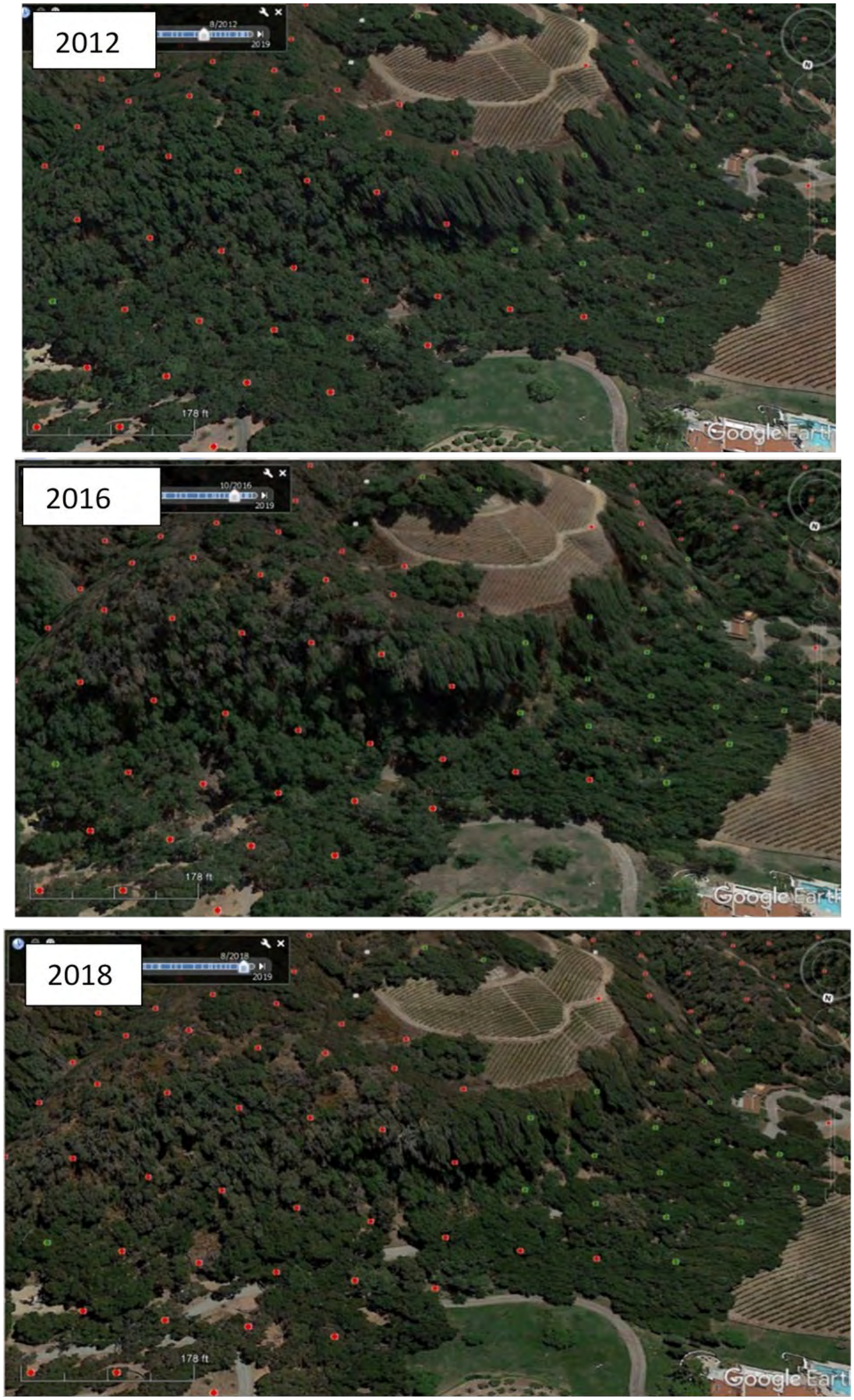


Figure 17b: 2012-2018 time series for visual inspection of pixels with 55% probability of having high dieback. Pixels with 95% probability of dieback would have provided a more graphic example of dieback

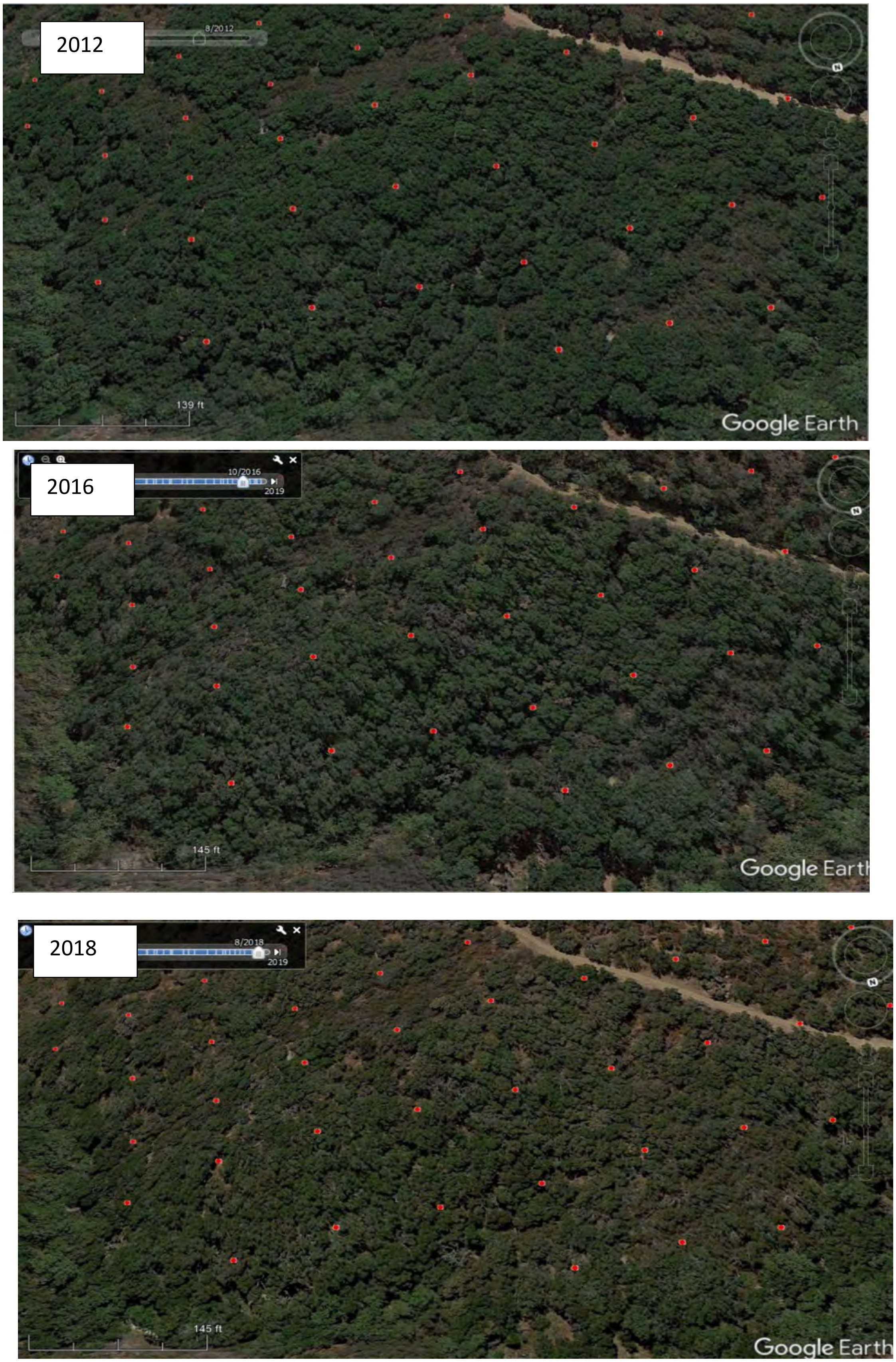


Figure 17c: 2012-2018 time series for visual inspection of pixels with 55% probability of having high dieback. Pixels with 95% probability of dieback would have provided a more graphic example of dieback

Field visit

We surveyed a number of oak woodlands in the mountains that had burned or experienced drought dieback in a field visit Sept 1-3, 2020.

Many trees recorded as dead in a survey after the 2016 Old Fire were actually resprouting in September 2020. While there was some mortality, it was much lower than the initial postfire assessment and even some of the trees that were cut back to a stump as a hazard after the fire, were resprouting. There were only a few *Q. lobata* skeletons and none were resprouting. In some cases, evergreen chaparral shrubs, like *Malosma laurina* and *Rhus ssp*., grew adjacent to the dead trunk or directly underneath the dead oak canopy which could easily lead to misinterpreting oak mortality in aerial imagery as oak recovery from resprouting.

Unburned oak sites were also visited. A large oak woodland at Topanga State Park showed severe dieback in Google Earth Imagery, but EVI values sometimes did not reflect that. During the field visit we found giant wild rye (*Eleymus condensatus*), a large perennial grass, formed a dense, continuous understory in the oak woodland at this location and that presumably contributed to the high EVI values.

In the unburned oak stands, some areas hit very hard by the drought had numerous oaks that had appeared dead at the end of the drought in 2018. At the time of our visit we saw major canopy and branch dieback, but most trees were resprouting, particularly epicormically from the trunk or major branches. Some had miraculous resprouting, for example one tree, in which all the main branches had fallen off, leaving just a ~7 ft stump, had new shoots sprouting from the top of the stump.

I estimated about 80 - 85% of the apparently "dead" trees in the burn and unburned drought impacted area were resprouting.

Fire and drought

While it would've been interesting to compare drought stress/response of oaks that burned during the drought to oaks that burned before the drought, it was not feasible considering the large pixel size of Landsat. The understory vegetation ends up driving the EVI value and gives a false sense of recovery.

The figures below show that some pixels that had complete canopy loss recovered to pre-drought/pre-fire greenness by 2018 and most had recovered by 2019 (**Figure 18**). Google Earth imagery (**Figure 19**) and field visits showed that this was not true. What the sensor was picking up was mostly understory vegetation.

Even 10m Sentinel imagery may not be high enough resolution to monitor regrowth, particularly of oaks with complete canopy loss (see **Figure 25**). The image shows that unless the pixels overlaps almost perfectly with the center of the oak, a lot of understory vegetation still dominates the pixel and will continue to give a false sense of recovery. Even if the pixel does overlap with oak regrowth, recovery may be underestimated since Kibler (2019) found that oak skeletons block about 25% of regrowing oak vegetation. However, this was for an oak species that only regrows from basal resprouts, so results may vary.

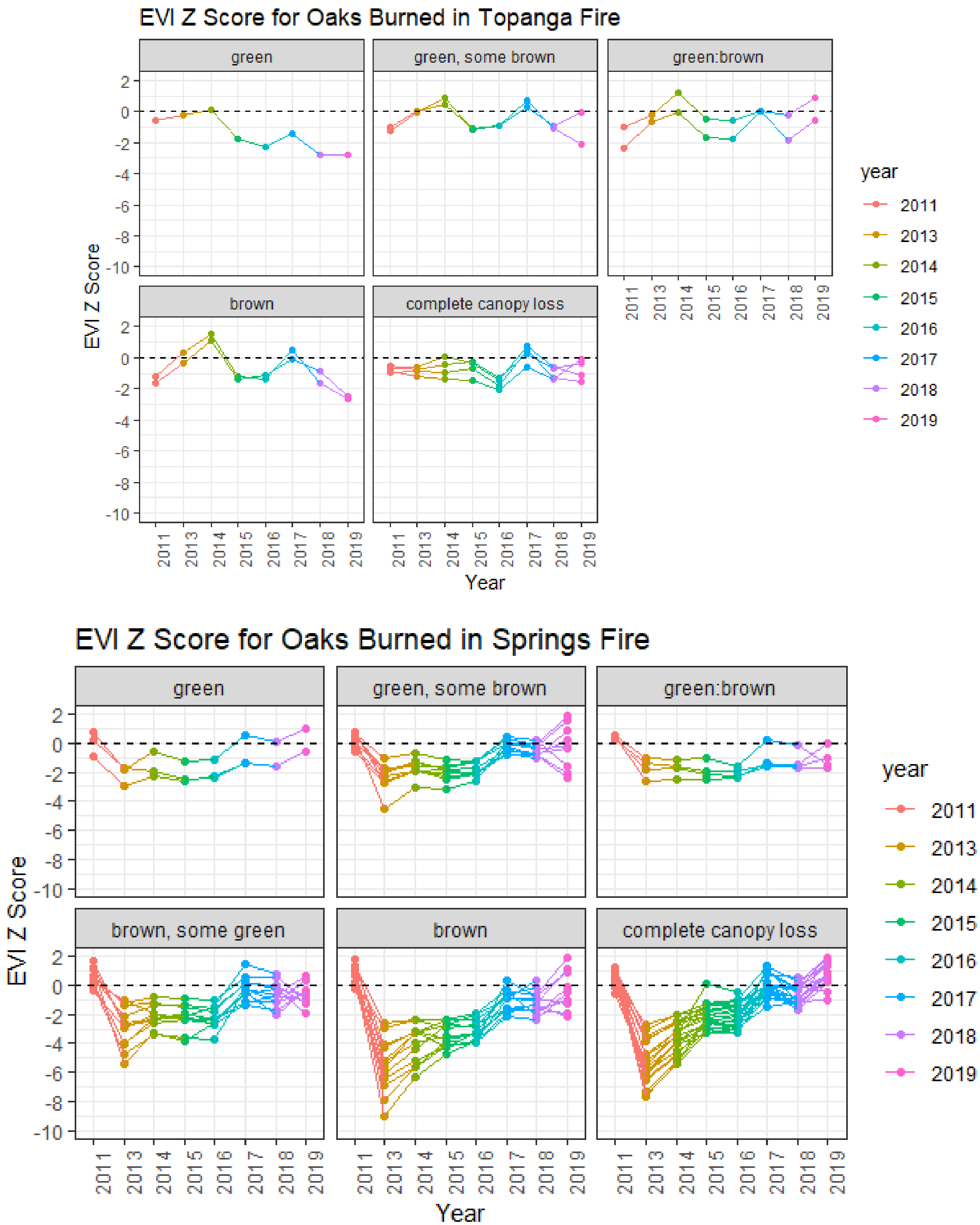


Figure 18: EVI Z scores of oaks burned in the 2005 Topanga Fire and 2013 Springs Fire with different levels of fire-induced canopy dieback. Topanga Fire had less heterogeneity in burn severity. I also do not trust my classification of canopy loss for the Topanga pixels since 2005 Google Earth imagery was not very good. The goal was to compare drought response of oaks that burned before a drought and oaks that burned during a drought to see how drought stress affected recovery or mortality.

a.

b.

Figure 19: (**a**) Shows a time series of oaks with severe canopy loss after the 2013 Springs Fire with lots of understory vegetation in 2018. (**b**) Shows an entire polygon in 2011 and then again after the 2018 Woolsey Fire. There was severe loss of oak canopy, yet the understory has very quickly grown back. This is an example of the difficulty in monitoring oak regrowth as the understory will drive the EVI trends.

Landscape position

I noticed that some pixels in ravines seemed to do better during the drought than those on angled slopes (**Figure 20 and Figure 21**). On average those on slopes seemed to do worse (**Figure 20**). When comparing the annual time series, they also seem to do worse, but when comparing EVI Z scores there does not appear to be a difference (**Figure 21**). I do not think this analysis warrants further study.

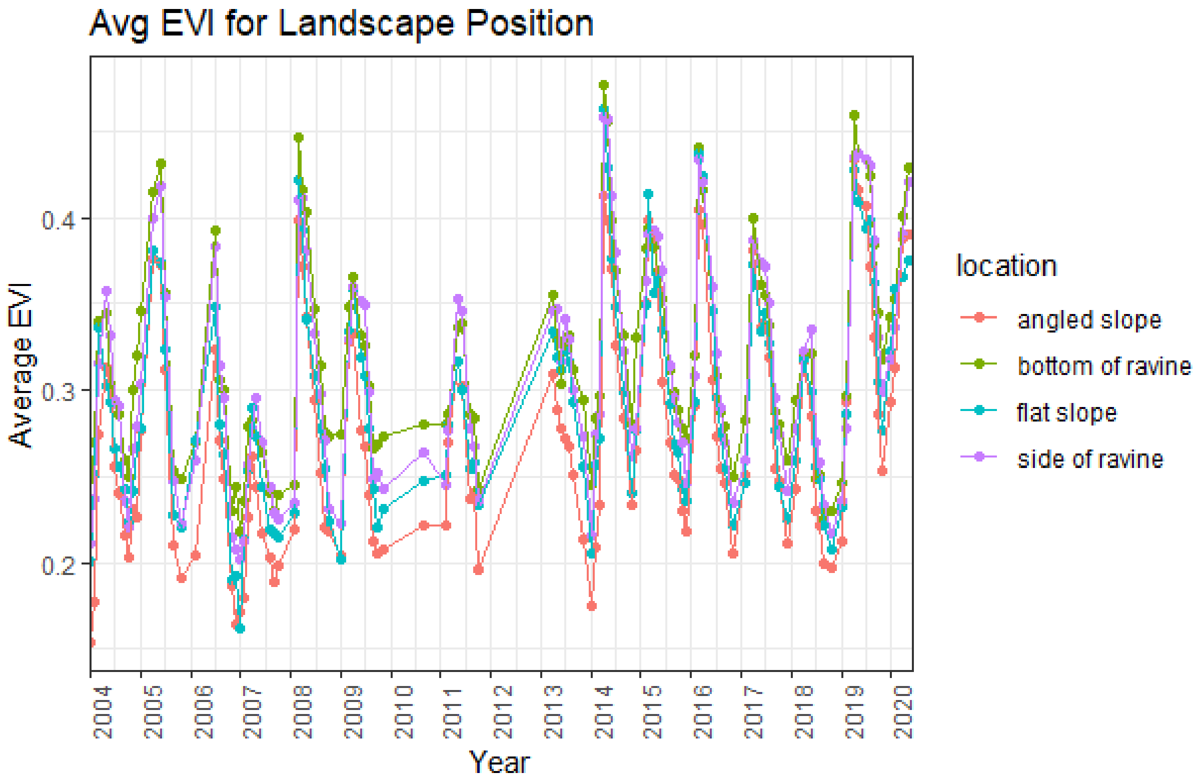


Figure 20: average EVI for landscape position. On average, pixels on angled slopes appear to have lower EVI.

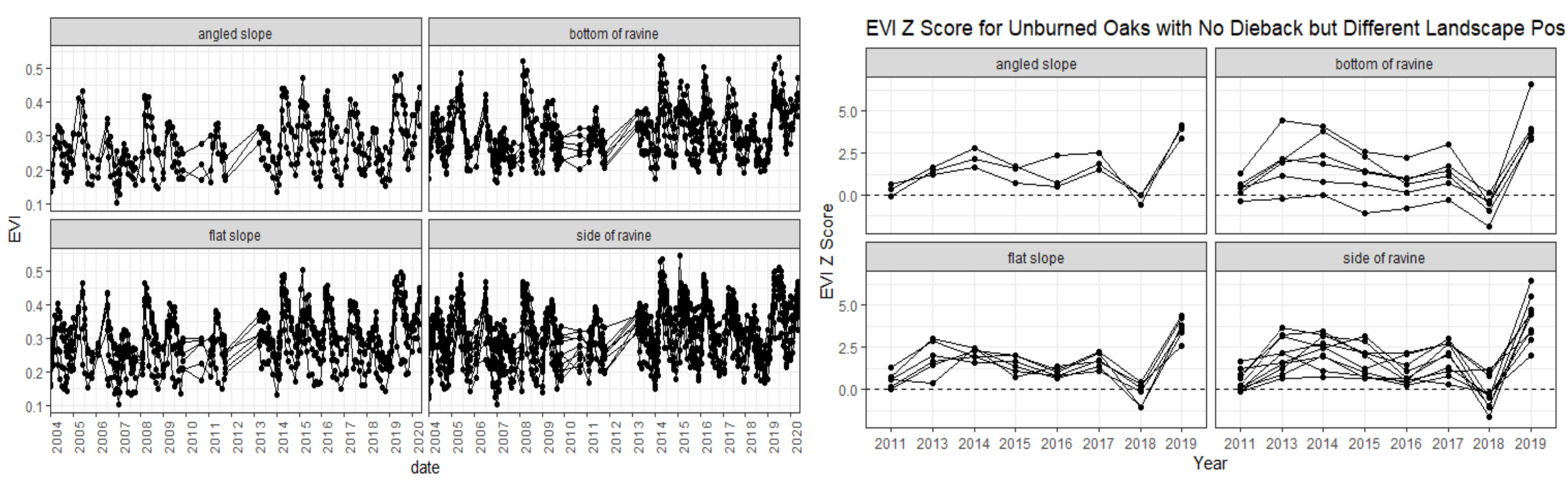


Figure 21: Comparing EVI time series to EVI Z score for oak pixels with different landscape positions. The left shows that there might be difference between landscape position and EVI, but the right shows that there is no distinguishable difference. (note: all pixels were classified as no dieback).

Predictor of future drought response

When looking at the time series of pixels with dieback after the 2011-2018 mega drought to the drought response of oaks during the severe, but short drought of 2006/2007 (year of very low rainfall) the drought response seemed similar. This made me wonder if the way an oak responds during a severe, but short drought would be indicative of how the oak responds to a more severe drought. If true, then how an oak responded to a recent mega drought might also be indicative how the same oak will respond to a future mega drought. This would enable SAMO to take preventative management actions by being able to pre-map oaks sensitive to drought induced dieback.

July 2006 had the peak EVI and December 2006 mostly had the lowest EVI values in the small sub-sample. I used the decrease in EVI between those months and compared it to 2018 estimates of dieback during the mega drought. At first, I only looked at pixels with high dieback and no dieback since I do not think my classification of pixels in the moderate dieback category was correct (**Figure 22**). I ran a Welch Two Sample T-test to determine if the mean decrease in 2006 July and December EVIs between pixels with no dieback and high dieback during the mega drought is statistically significant. (I did not check the assumptions to use a Welch's Two Sample T-Test). I got a p-value of 0.053, so I fail to reject my hypothesis.

I then increased the sample size by combing the pixels in the moderate and high class together since most pixels in the moderate class would qualify for high dieback (**Figure 22**). I re-ran the Welch Two Sample T-test to determine if the mean decrease in 2006 July and December EVIs between pixels with no dieback and combined high/moderate dieback during the mega drought is statistically significant. (I did not check the assumptions to use a Welch's Two Sample T-Test). I got a p-value of 0.0001.

Due to these contrasting results, I think this analysis warrants another look with a larger sample using pixels whose dieback is more confidently assessed.

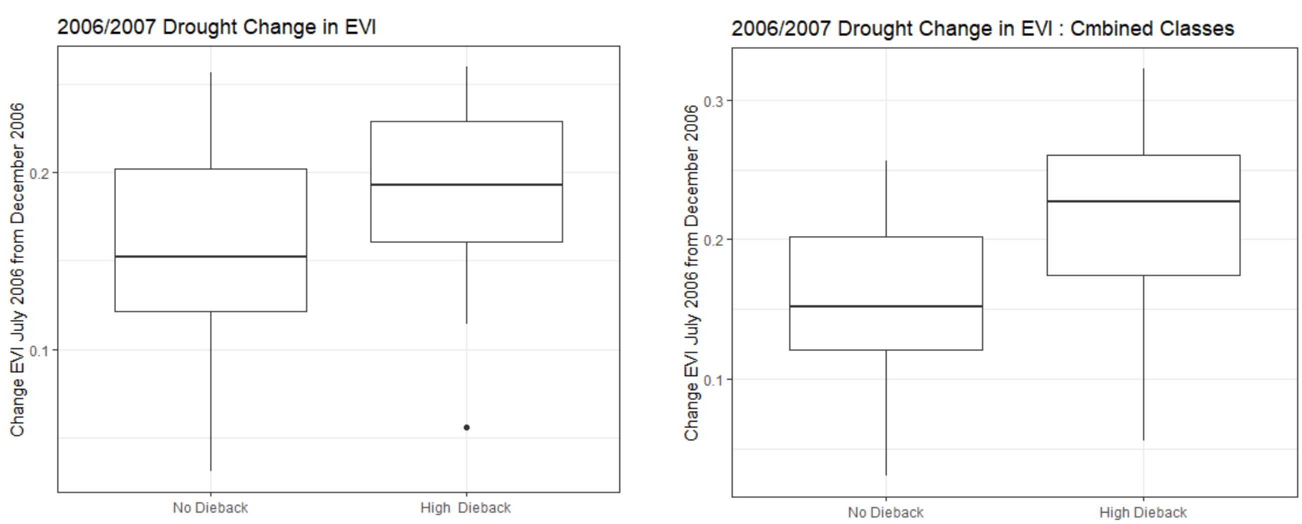


Figure 22: Left figure shows the range of delta EVI values for just high and no dieback. Right shows the same except the moderate and high dieback pixels were grouped together to increase the sample size.

Moderate dieback assessment

This section answers the second research question: Can the method I choose, which uses 30-m Landsat imagery with EVI, distinguish between different severities of oak dieback? No, it cannot. 30-m pixels have too much heterogeneity within the pixels. Higher resolution imagery will likely be able to better distinguish different severity types since there will be less heterogeneity within pixels.

I classified 25 pixels as having moderate dieback, but after plotting their EVI values (**Figure 23 a and b**) I second-guessed my dieback classification. Upon further examination of the pixels, I think more would classify as high dieback rather than moderate dieback. Only a few pixels looked as though they had moderate dieback (**Figure c**) and the trend was very similar to pixels with no dieback (**Figure 23 d**). It was hard to find more pixels with this dieback type because I was both short on time but also because many pixels would have moderate oak dieback in half the pixel but the other half of the pixel would be annual grass or no dieback. I think higher resolution imagery would help with this. I also think an objective, quantitative method for classifying dieback would be best. Although tedious, it would make the results more robust and the classification method could not be criticized as biased or inconsistent.

Email me (aparkinson@bren.ucsb.edu; [amlparkinson@yahoo.com)](mailto:amlparkinson@yahoo.com) for the program to calculate classification area in aerial imagery. It essentially overlays several little box onto an image so users can classify things like green vegetation vs non-green vegetation or dieback vs no dieback. It can also be used to quantify proportion of dieback in a pixel. Keep in mind it would be a tedious process; it potentially could be a project for undergraduate research training. Hopefully higher resolution imagery won't have this same problem and vegetation cover in pixels will be more homogenous. In the end I just used pixels classified as high dieback (n=25) and no dieback (n=25) because those two classifications are very obvious.

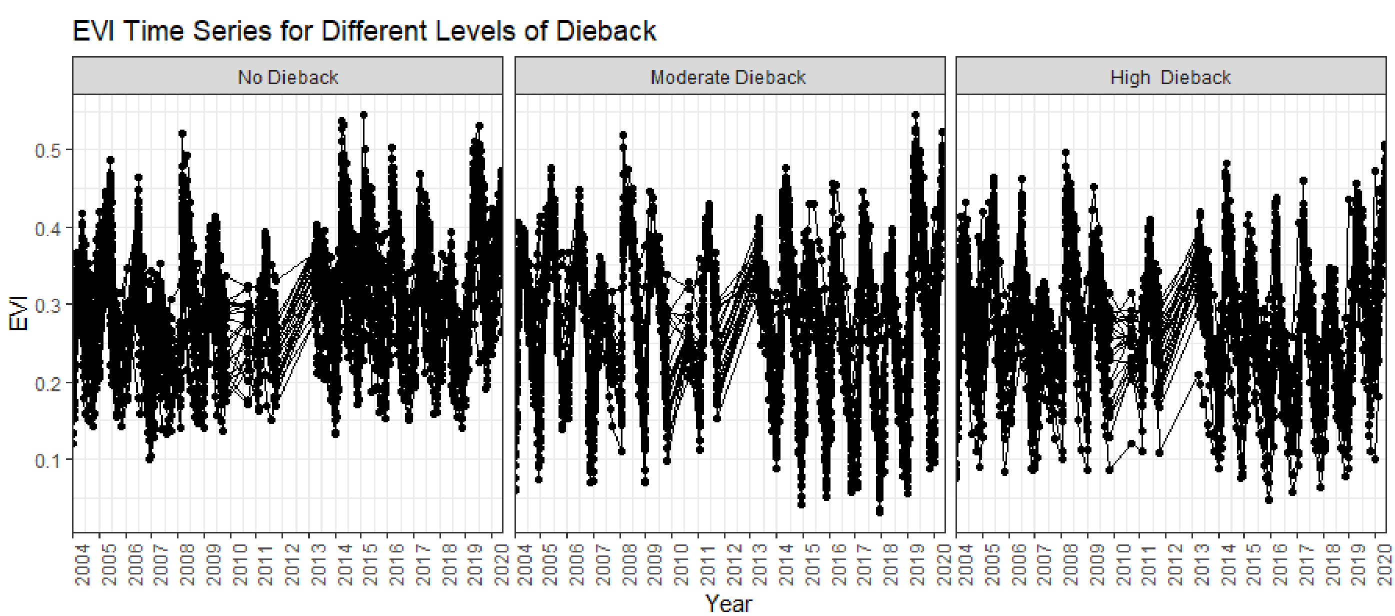


Figure 23a: EVI time series for pixels with different manual classifications of dieback. It was concerning when pixels with moderate dieback had lower EVI value than pixels with high dieback.

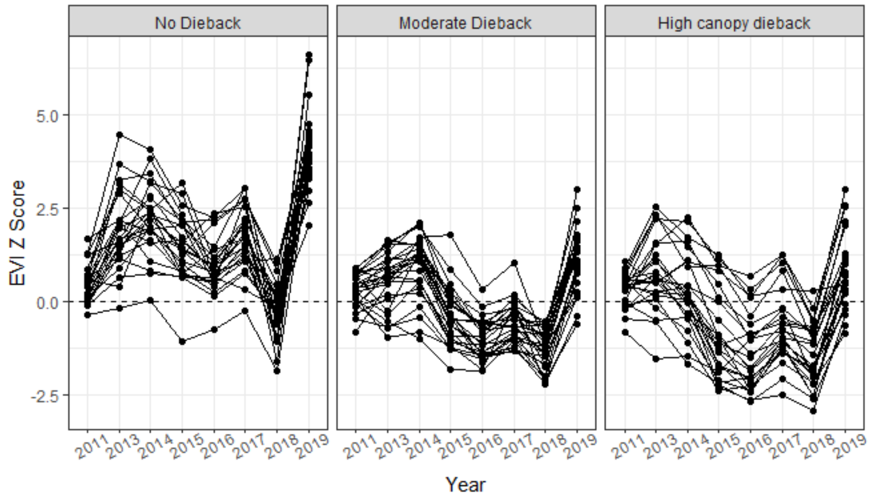


Figure 23 b: EVI Z score of pixels with different classifications of dieback.

Figure 23c: pixel with moderate dieback. Moderate dieback is when the tree does not necessarily die, but the canopy does visibly open due to dropped branches or dropped leaves.

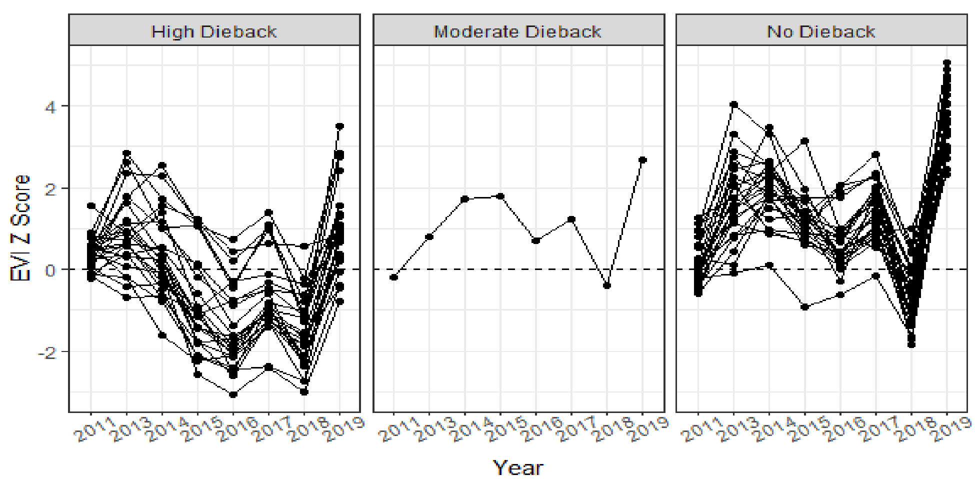


Figure 23d: the pixel in **Figure c** is the one plotted in the middle graph. The trendline is very similar to pixels with no dieback.

Comparison to NASA methods and results

NASA group II only identified 2,163 acres of oak woodlands in the park, which they said were "slightly different from the NPS data" (**Figure 23 and Figure 24**). I got 8,243.5 acres from the NPS 2007 vegetation layer. After applying the pixel removal thresholds, I identified 5,218.8 acres.

NASA team II used Relative Fraction Alive Vegetation (RFAL) from AVIRIS imagery to monitor drought. RFAL "reflects the percent of green vegetation divided by a total of green vegetation plus non-photosynthetic vegetation" (NASA group II). These values were then validated using the 2016/17 observed condition of the 25-m^2 field plots which were surveyed in September/October. These data were averaged to find the RFAL that corresponded with a field plot condition of 3.2 (55% dead), which was identified as the threshold for dieback. Trees in this condition are declining and not expected to recover.

The RFAL threshold value was found to be 0.5431, with an R^2 value of 0.0251 (**Table 9**). The low R^2 value can be attributed to the low sample size of plots (n=22) and to the difference in data collection times. The AVIRIS imagery was taken in June, while the field plot data was recorded from September to October.

Table 7. Summary of alive and dead acres of oak woodlands and riparian woodlands in the SMMNRA 2013-2016 (based on RFAL calculated by NASA DEVELOP team)

Vegetation Type	Acres alive 2013	No. trees alive 2013	Acres dead 2013-2016	No. Trees Lost 2013-2016
Annual grass	26634		16391	
C. megacarpus	3445		726	
C. spinosa	1839		141	
Chaparral	16754		2931	
Coastal sage scrub - drought decidous	27044		10851	
Coastal sage scrub-summer active	12795		4408	
M. laurina	35091		9865	
Oak woodland	2700	151,200	163	9,128
Riparian woodland	10514	367,990	3258	114,030
TOTAL acres	**110183**		**32343**	

Table 9: NASA II group estimate of oak dieback using MESMA and RFAL.

For several reasons, I have concerns about the results of the NASA teams: use of June imagery, underestimate of number of oak acres, R^2 value had no relationship to on the ground dieback, and inconsistent numbers in their reports. The NASA team identified 2,163 acres of oak woodlands, but state there are 2,700 acres in a later table. They found 163 acres of oaks died between 2013-2016. This is convenient for comparison because I used 2016 to classify dieback. I estimated 2,053 – 3,466 acres had high dieback by 2016. For several reasons, previously mentioned, I think their method underestimated oak dieback. Even though my threshold had high accuracy (compared to their R^2 value of 0.025), I believe I am over-estimating dieback. I think a larger, more random sample to assess a threshold is needed and or higher resolution imagery. Unfortunately, I cannot find a RFAL map of the oaks estimated to have died by the NASA team, just a table, so I cannot compare locations of suggested dead trees.

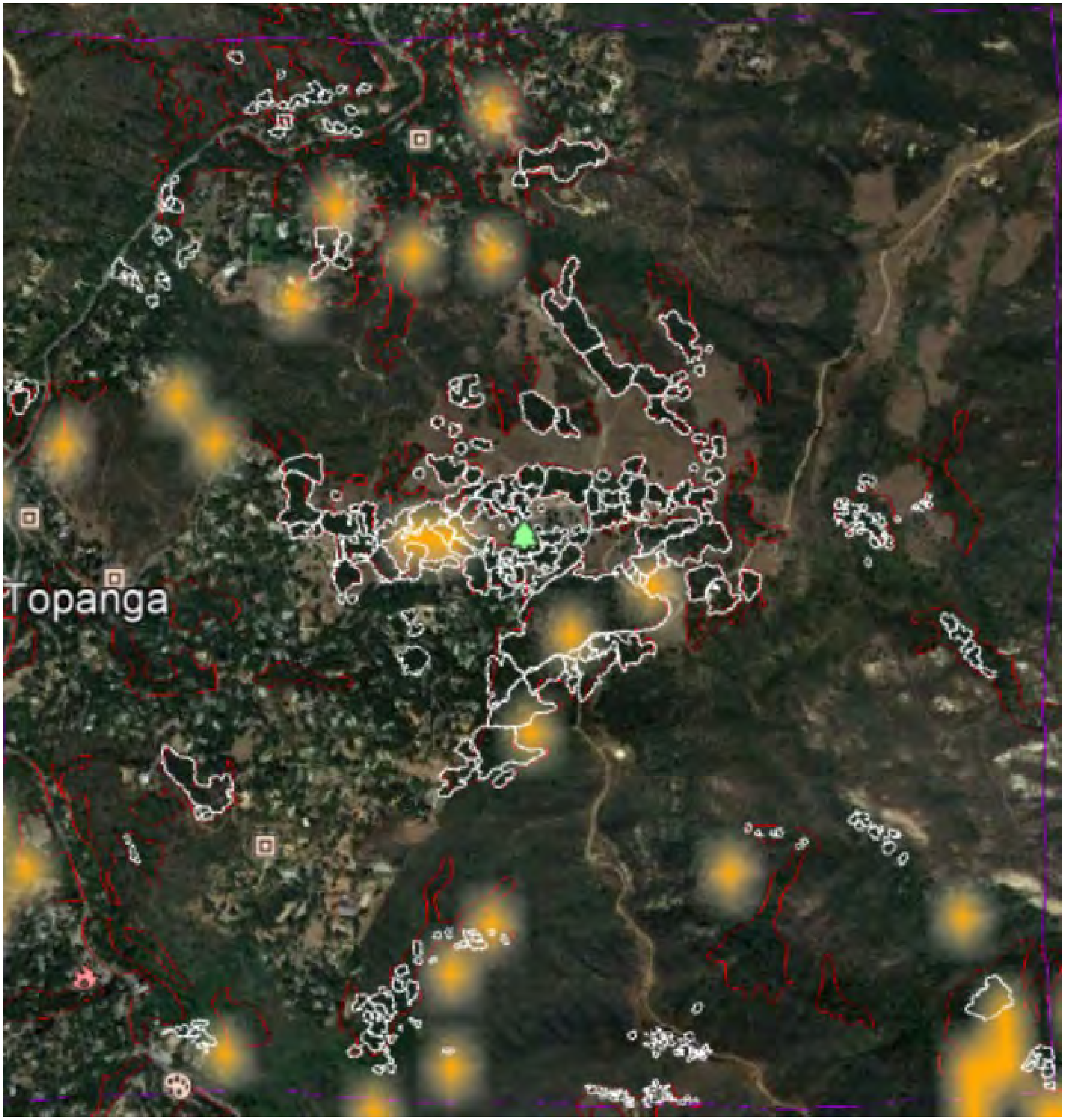


Figure 23: Quick comparison of oak polygons from the 2007 SMMNRA Vegetation Map (red), the MESMA identified oak pixels (orange) by the NASA group, and my classification of oak stands using Google Earth imagery (white; note I did not finish identifying all oaks in the area as it was hard to distinguish oaks from riparian trees and other vegetation. Additionally, some of the white polygons overlap the boundaries of the red polygons).

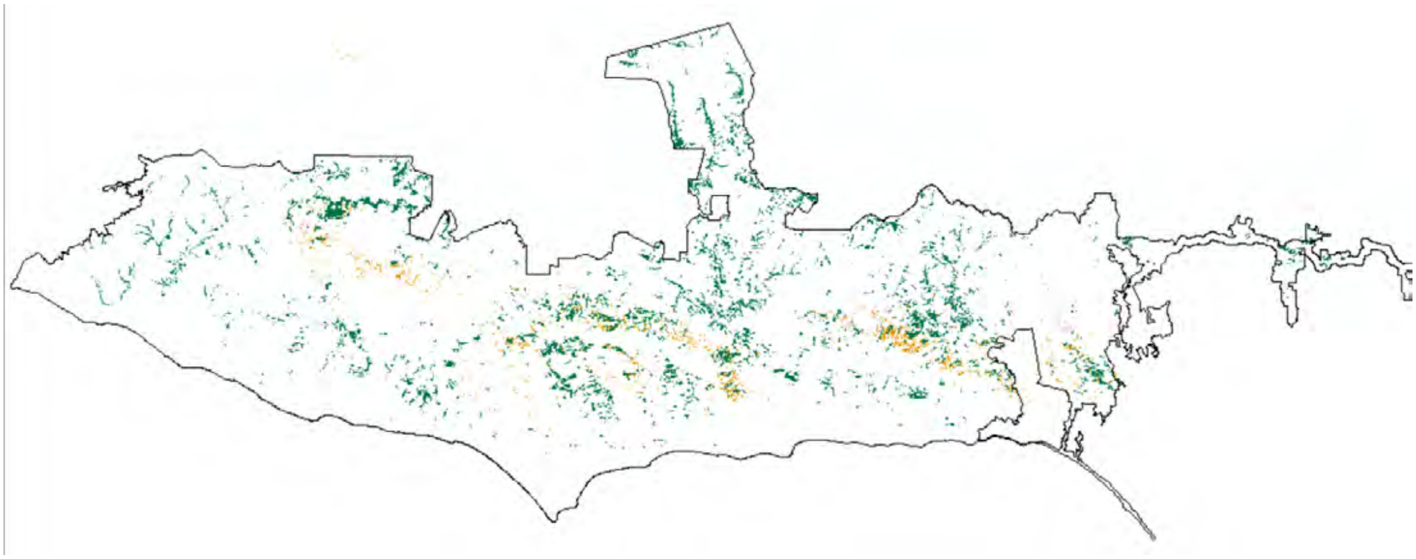


Figure 24: Landscape view of oaks classified by NASA MESMA (orange) and the 2007 SMMNRA Vegetation Map (green).

CONCLUSIONS

Summary

- Oaks are very resilient! While oaks experienced canopy dieback and apparent mortality during the drought, many have been observed resprouting new growth.
- Most oaks with dieback experienced notable decrease in EVI three years into the drought after 2014. But oaks with no dieback did not have noticeable loss in EVI until seven years into the drought in 2018 and they had a much larger increase in EVI after the drought in 2019.
- My model estimates that 2,053 – 3,566 acres (45.6% - 77%) of unburned oaks had a 95% - 50% probability of high dieback as a result of the 2011-2018 drought. I believe this number is an overestimate. More likely it could indicate pixels that had moderate and high dieback.
- How oaks respond to short intense droughts may be an indication of how the oaks respond to more prolonged, severe droughts. While a larger sample size is needed to confirm these results, this could mean that how oaks responded to the recent megadrought will be indicative of how they will respond to future mega drought (i.e. oaks that performed well in 2011-2018 drought, will likely perform well in future droughts).
- While using 30-m Landsat imagery and a simple greenness index performed well in accessing dieback, higher resolution imagery is needed to assess moderate dieback as there will be less heterogeneity within pixels.
- More work is needed to monitor post-fire and post-drought oak growth.

Recommendations for improvement in my approach

- *A larger sample is needed* to improve the accuracy assessment of the dieback binomial model.
    - Test data should be randomly selected and from all areas of the park. My original test data was from the same general area and the trendlines showed a very clear distinction threshold between oaks and other vegetation, but once I used my random test data that clear threshold was no longer applicable.
- *Incorporate factors such as the Normalized Difference Water Index (NDWI)* or topography into the dieback threshold to see if that increases model accuracy.

- *Try using an objective pixel removal threshold*. I picked values by looking at the graphs, but it would be interesting to try a similar approach that was used to pick the threshold for dieback and see how the results compare. Machine learning could be used, but that can be very time consuming. Neither may be necessary if higher resolution imagery is used.
- *Use a longer baseline period*. If this is done, one will have to decide how to include burned oaks since those top-killed, with complete canopy loss, can take decades to recover.
- *Create random test data* to check the accuracy of the dieback threshold. This would also be a good way to get new, larger, and randomly selected dieback data to rerun the dieback threshold binomial model.

<u>Recommendations for future research</u>

- *Compare accuracy and results using imagery with higher resolution*: 30-m Landsat v 10-m Sentinel-2 v 5-m (e.g.,) RapidEye v ~1m Worldview. A key question is how well higher resolution imagery would do and if certain steps could be modified or eliminated (e.g. one step pixel removal threshold instead of two steps; does increased resolution increase accuracy?).
- *Incorporate lidar data:* While lidar is not dependably available either spatially or temporally, that is expected to improve in the future. Evergreen chaparral shrubs are the most likely vegetation type to confound oak detection with remote sensing spectral or imagery methods. Lidar has been successfully used to separate tree and shrubland vegetation types based on their height differences in postfire mapping of vegetation recovery in the Angeles National Forest (Angeles National Forest 2019, see Resources folder).
- *Analyze landscape scale trends in dieback:* From our field surveys, we observed that oaks can survive severe drought, drought and fire, drought and fire and more drought. What does drive dieback of oaks? Are there any topographic or climate variables that can predict oak dieback? Or is dieback dependent on the tree itself? This analysis would first require refining the work I did (e.g. incorporating NDWI or Lidar into the dieback threshold, using higher resolution imagery) to make the results more robust. The NASA groups did some work like this, but the climate variables they used were very coarse, and some relationships with very weak R^2 values (e.g., $R^2 = 0.025$) were used to draw conclusions. The use of June imagery for their analyses, rather than fall or September when plants are most stressed, further complicates useful comparisons and reliable conclusions from their work.
- *Interaction of fire and drought:* This would require higher resolution imagery, but even then, it may be a very hard analysis to do. Monitoring post-fire growth of vegetation like oaks is no easy task; one that researchers have struggled with. Some of the issues I see are:
    - The post-fire pixels may have to be hand selected to ensure they really overlap with the oak skeleton, otherwise it is the understory that will be measured (**Figure 25**). Perhaps Lidar can be used to help with this issue.
    - The presence of understory vegetation will still be a problem, so how can understory regrowth be distinguished from oak regrowth? Communications with Chris Kibler revealed that while MESMA can theoretically be used to calculate the fraction of oak vegetation within a pixel in order to monitor regrowth, it would require A LOT of calibration (**Supplemental 3**).
    - Kibler 2018 found that oak skeleton cover was ~25% of regrowing oak canopy 11 years post fire, so oak regrowth was being underestimated.

  I can see this being a project dependent on test data that could provide interesting results, but I am unsure how well it could be applied it to an entire landscape, particularly because of my first point of needing to manually ensure selected pixels overlap the oak canopy.

  Until dieback and recovery can be accurately measured, it is very difficult to determine how elements of fire (severity, time between fires (fire return interval), number of fires) and drought interact to affect oak mortality. For example, do oaks with higher burn severity in a fire during or followed by drought have higher mortality? Do oaks that burned before, during or after drought have faster/slower recovery or dieback probabilities?

- *Redo NASA MESMA analysis by applying the spectral library to Landsat imagery*: This would ensure the methods are consistent with my study which would enable comparisons between my simple approach to a more advanced approach that would require advanced expertise. The NASA group only used AVIRIS imagery which can be an issue because of the limited temporal coverage available. They used early summer/late spring imagery to monitor dieback but vegetation like annual grasses and sub-shrubs in the understory can still be green. Both my approach and the MESMA approach use a greenness index (EVI vs green vegetation fractions). The question is whether the specialized analysis would improve accuracy above the simple EVI approach, or is the problem one of imagery resolution rather than analytical method?

  The NASA group spectral library is available in the Spectral library folder. It was created by recently graduated undergraduates, so it may be worthwhile to compare it to the spectral library created by Christopher Kibler in Dar Robert's lab. His data was developed for Los Padres National Forest (additional information on his methods are in Kibler Master's Thesis 2019 in the Resources folder), but while it is not quite ideal, he said it can be used for other regions (see **Supplemental 3**). Additionally, the ANF has another spectral library developed by NASA JPL for postfire monitoring that is available (ANF 2019).

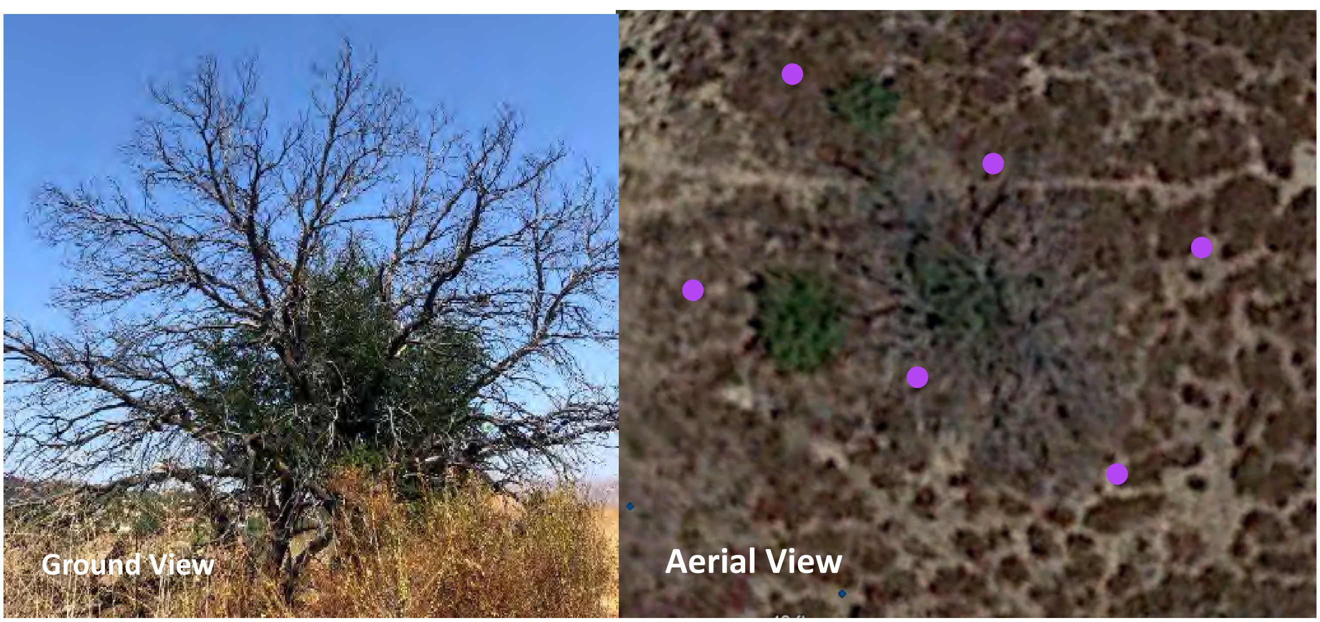


Figure 25: Ground vs aerial view of a resprouting oak from the 2016 Old Fire. The two green shrubs on the right of the skeleton are not oaks. The purple dots are pixel centers of Sentinel-2 imagery. It looks like the oak regrowth will be split between the two center pixels. The bottom far right pixel partially covers the oak skeleton, but there is no regrowth and there is a lot of understory in the pixel.

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SUPPLEMENTALS

Supplement 1: Satellite Imagery Review

Most information on satellites can be found here: https://www.satimagingcorp.com/satellite-sensors/quickbird/

- **NAIP**: available at earth explorer → data sets→aerial imagery; should be 1m resolution but it doesn't seem like it. Maybe it will if I request an image and zoom in in another app. Beginning in 2003, NAIP was acquired on a 5-year cycle. 2008 was a transition year, and a three-year cycle began in 2009. The most recent year is 2020. Should download the imagery and compare to Google Earth Imagery. https://www.fsa.usda.gov/programs-and-services/aerial-photography/imagery-programs/naip-imagery/
- **Advanced Very High-Resolution Radiometer (AVHRR):** provides four- to six-band multispectral data from the NOAA polar-orbiting satellite series. There is fairly continuous global coverage since June 1979, with morning and afternoon acquisitions available. The resolution is 1.1 kilometer at nadir. From earth.explorer
- **IKONOS and OrbView:** not available in study area; earth explorer
- **MODIS GPP**: earth explorer; 500m resolution (VERY coarse!)
- **MODIS evapotranspiration**: earth explorer; 500m resolution (VERY coarse!)
- **Sentinel 2**: earth explorer; only launched in 2015…or 2017, resolution 10-20m; https://www.usgs.gov/centers/eros/science/usgs-eros-archive-sentinel-2?qt-science_center_objects=0#qt-science_center_objects
- **rapideye**: 5m resolution; spectral bands: blue, green, red, red edge, nir (no swir); available from 2009. Retired the satellite in 2020, so not sure if they launched a newer one or not…
    - **applied for access for RapidEye imagery freely available in the ESA archive**, which can be accessed here. BUT there is not free imagery available for the study area (looked for years 2004-2019). There's barely any available for the US.
    - The NASA III group said their imagery was 'acquired from Planet Team (2019)'
    - Made a planet account, but I can only look at the imagery I cannot download it. Need a paid account. Maybe NASA has one and our contacts can get the imagery for us.
- **AVIRIS**: 15.6m resolution; available from NASA JPL contacts?
- **Lidar**: LiDAR paired with the DEM provided information used to calculate a Canopy Height Model (CHM), and canopy density for a limited geographic subset of the study area in Trippett Ranch, part of Topanga State Park; lidar from la county = 1m resolution; Lidar data are already widely available, but a spaceborne Lidar was installed on the International Space Station in 2018 and so canopy height measurements can now be made even where no aircraft Lidar are available.
- UAVSAR data: downloaded …through JPL's UAVSAR Data Portal. These data provided an ideal spatial resolution (1.8m). Data was collected annually for the study area, but at inconsistent times/seasons.
- DESIS, on the International Space Station and scenes on request using these data will continue to be available from additional sensors, HISUI, from Japan and EMIT from NASA until the late 2020s
- Worldview 3: launched 2014, bands=red, red edge, blue, green, yellow, nir1, nir2, swir; resolution=0.31-3.7m depending on the bands used
- Worldview 2: launched 2009, bands=red, blue, green, near-ir, yellow, nir-ir2; resolution =0.46-2.4m depending on the bands used; data available through USGS, which is free(?) for government employees→ just need to fill out a form. See here. Not sure how long approval will take though. This link also has a shapefile of the satellites path, and SAMO falls within the satellite flight path.
- Quickbird: available 2001-2014, bands=blue, green, red, near ir; resolution=0.65-2.6m depending on bands used

- Ikonos: 1999-mid 2000s
- Triplesat: launched 2015
- Spot 7: launched 2014, bands=b,g,r,nir; resolution =6m
- Spot 6: launched 2012, bands=b,g,r,nir; resolution =6m
- TerraSAR-x: launched 2007, bands and resolution = ?? (Russian)
- Jilin-1: unknown info (Chinese)
- SkySat1 and 2: launched 2014, bands=b, g, r, nir; resolution=1.1m
- TripleSat: launched 2015, bands=b, g, r, nir; resolution=3.2-4m
- Gaofen: Chinese
- Kompsat3: launched 2012, bands=b, g, r, nir; resolution=2.8m (not American)
- Superview: launched 2018 (Chinese)
- Pleiades 1B: launched 2012, bands=b, g, r, nir; resolution=1-3m
- Pleiades 1B : launched 2011, bands=b, g, r, nir; resolution=1-3m
- Formosat-2: launched 2004-?? (decommissioned), bands=b, g, r, nir; resolution=8m
- TH-01: launched 2010, bands=b, g, r, nir; resolution=10m
- ALOS: launched 2006, bands=b, g, r, nir; resolution=10m
- cartosat: launched 2005, bands=?; resolution=2.5m (Indian)
- spot-5: launched 2002-2015, bands=b, g, r, nir, swir; resolution=10m (but swir=20m)
- dove: launched ??, bands=b, g, r, nir; resolution=2.7-4.9m
- sentential 2A: launched 2015; bands=b,g,r,nir, swir I, red edge, swirII; resolution=10m (swir and red edge=20)
- ASTER: launched 1999, bands=Visible NIR, swir, thermal IR, resolution =15, 30, 90 respectively.
- Cbers-2: launched 2001 (Chinese); 20+meters
- Sentinel 1: Launched 2014
- Envisat: failed in 2012
- ERS 1 and 2: launched early 1990s, mission ended late 1990s/early 2000s
- G-LiHT: portable, airborne imaging system that ***simultaneously*** maps the composition, structure, and function of terrestrial ecosystems; resolution=1m; NASA, data available for download, but no flights were conducted in our study area
- ICESat: NASA satellite to collect satellite flown lidar? Launched 2003, decommissioned 2009 or 2010
- ICEsat-2: launched 2018

Panchromatic images are produced by satellites such as Landsat, DigitalGlobe's range of satellites and SPOT6/7. Such images have a single band that "combines" the information from the visible bands of blue, green and red. In other words, the band is formed by using the total light energy in the visible spectrum (instead of partitioning it into different spectra). It renders a single intensity value per pixel that is commonly visualized in a greyscale image. Information contained in each pixel of a panchromatic image is, therefore, directly related to the total intensity of solar radiation that is reflected by the objects in the pixel and is detected by the satellite sensor. **https://www.stars-project.org/en/knowledgeportal/magazine/remote-sensing-technology/introduction/multispectral-and-panchromatic-images/**

Satellite Imagery sources:

- https://intelliearth.harrisgeospatial.com/?_ga=2.45202276.1359326593.1595526493-1689705860.1595526493 can view and request imagery from several of the above satellites, but it cost $
- https://tpm-ds.eo.esa.int/oads/access/collection --> some of the above sources are available in the European Space Agency (ESA) archive.
- **Worldview 1, 2, and 3:** data available through USGS, which is free(?) for government employees→ just need to fill out a form. See here. Not sure how long approval will take though. This link also has a shapefile of the satellites path, and SAMO falls within the satellite flight path. Also available from ESA, but only available after project proposal acceptance.
- **Lidar** (Ventura and LA County): https://coast.noaa.gov/dataviewer/#/imagery/search/-13260371.699943239,4027139.8767962945,-13184424.762539834,4066178.014143643 → this site does not have satellite imagery
- Sentinel 2: https://earthexplorer.usgs.gov/
- Landsat: https://earthexplorer.usgs.gov/
- Earthdata: NASA website. Doesn't seem too helpful. Unfriendly user interface.
- The National Map: from USGS https://viewer.nationalmap.gov/basic/

Supplemental 2: Fire and Drought Matrix

All fires that had drought had relatively high number of pre and post fire drought months, except the Woolsey Fire. This means that there is a limited ability to distinguish whether prefire or postfire drought stress, or both, were responsible for any observed impacts on mortality and postfire recovery (**Table S2-1**).

Based on **Table S2-1**, I created a matrix of the coincidence of fire and drought before and after fires. The matrix shows the number of oak polygons with drought before and after the fire, and polygons with fire but no drought before or after the fire, and unburned polygons (**Table S2-2**) .

There was a small gap between the end of the mega drought and when the Woolsey fire started (**Figure 2, page 4, PDSI graph**) so the Woolsey fire was classified as fire-no drought. However, The Woolsey fire would be more correctly classified as fire-prefire drought, postfire no drought.

I would recommend that the matrix of the number of polygons with different combinations of fire and drought be recalculated to classify the oak polygons (**Figure S2-2**) as follows: 1) the Woolsey fire as fire and pre-drought, 2) the Corral, Springs, and Old fires as fire and pre-post-drought, 3) fire and no drought and 4) no fire.

Table S2-1: Drought conditions measured by number of months of negative PDSI before and after significant fires. Fire_year_precip = the amount of rainfall that occurred the calendar year of the fire.

Filter

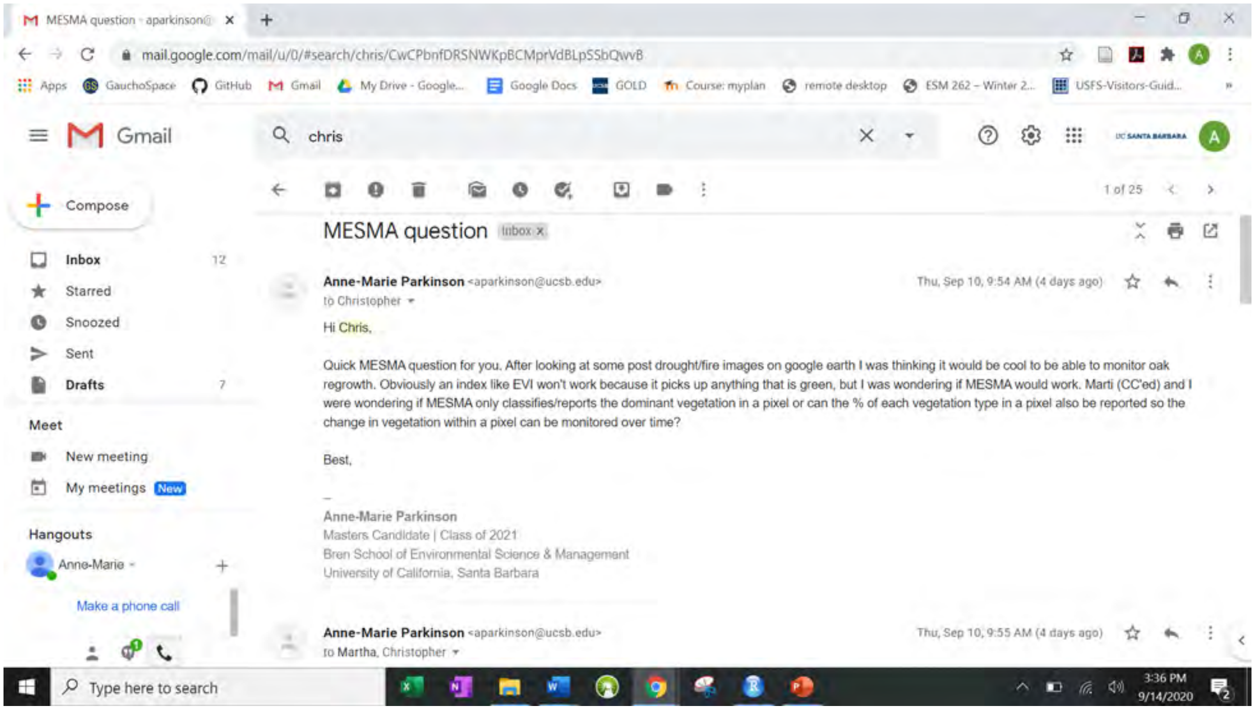
fire_name	fire_name_mod	months_prefire_drought	months_postfire_drought	fire_year_precip
Topanga	Topanga	0	0	32.14
Corral	Corral	11	25	9.31
Springs	Springs	15	27	7.22
Old	Old Fire 2013	18	24	7.22
Old Fire	Old Fire 2016	15	21	9.07
Woolsey	Woolsey	0	0	16.98

Table S2-2 Matrix showing the number of oak polygons with drought before and after the fire, and polygons with fire but no drought before or after the fire, and unburned polygons. The Woolsey fire was classified as fire-no drought, but would be more correctly classified as fire-prefire drought.

Filter

	pre_drought_qualitative	fire_qualitative	n
1	Drought	Fire	267
2	No Drought	Fire	1048
3	NA	No Fire	865

Supplemental 3: Communications with Christopher Kibler, UCSB Department of Geography



MESMA question

Anne-Marie Parkinson <aparkinson@ucsb.edu>
to Christopher
Thu, Sep 10, 9:54 AM (4 days ago)

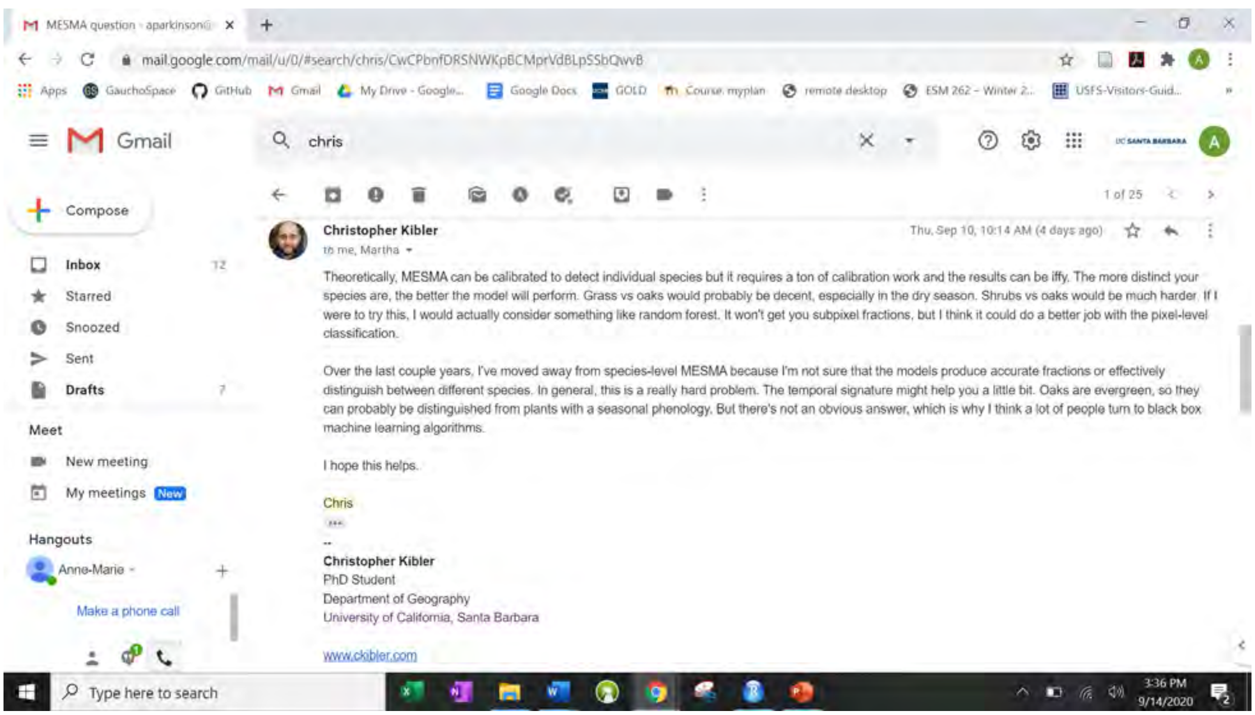
Hi Chris,

Quick MESMA question for you. After looking at some post drought/fire images on google earth I was thinking it would be cool to be able to monitor oak regrowth. Obviously an index like EVI won't work because it picks up anything that is green, but I was wondering if MESMA would work. Marti (CC'ed) and I were wondering if MESMA only classifies/reports the dominant vegetation in a pixel or can the % of each vegetation type in a pixel also be reported so the change in vegetation within a pixel can be monitored over time?

Best,

--
Anne-Marie Parkinson
Masters Candidate | Class of 2021
Bren School of Environmental Science & Management
University of California, Santa Barbara

Anne-Marie Parkinson <aparkinson@ucsb.edu>
to Martha, Christopher
Thu, Sep 10, 9:55 AM (4 days ago)



Christopher Kibler
to me, Martha
Thu, Sep 10, 10:14 AM (4 days ago)

Theoretically, MESMA can be calibrated to detect individual species but it requires a ton of calibration work and the results can be iffy. The more distinct your species are, the better the model will perform. Grass vs oaks would probably be decent, especially in the dry season. Shrubs vs oaks would be much harder. If I were to try this, I would actually consider something like random forest. It won't get you subpixel fractions, but I think it could do a better job with the pixel-level classification.

Over the last couple years, I've moved away from species-level MESMA because I'm not sure that the models produce accurate fractions or effectively distinguish between different species. In general, this is a really hard problem. The temporal signature might help you a little bit. Oaks are evergreen, so they can probably be distinguished from plants with a seasonal phenology. But there's not an obvious answer, which is why I think a lot of people turn to black box machine learning algorithms.

I hope this helps.

Chris

--
Christopher Kibler
PhD Student
Department of Geography
University of California, Santa Barbara

www.ckibler.com

Anne-Marie Parkinson <aparkinson@ucsb.edu>
to Christopher
Thu, Jul 16, 3:48 PM

Hi Chris,

My internship with NPS is under way and we are starting to narrow down our direction (I know, a little late. Long story). Anyway, they are interested in the best method for monitoring long-term fire and drought induced mortality and decline of oaks (just interested in the tall oaks like agrifolia and valley oak, not berberidifolia; there's no chrysolepsis in the park). Surprisingly, there is not a lot of work using remote sensing to monitor oaks. People really prefer using field surveys. Since you had experience with monitoring oaks using remote sensing with the NFWF project I wanted to get your opinion on an idea I had. The NPS people I work with liked it, but I want to make sure it is feasible before proceeding.

I have polygons of oaks, but that doesn't mean the entire polygon is covered entirely by oak. As you know, there could be spaces between oaks where grasses or shrubs grow, which can influence the remote sensors, especially after a fire. So I was thinking of using Lidar to identify where individual/groups of oaks are located. My thinking being, if we know exactly where the oaks are within these polygons (ie which pixels contain oaks), then high resolution imagery can be used to monitor drought affects and post-fire recovery with a high percentage of confidence that the signals we are seeing belong mostly/entirely to oaks and not the pesky understory. I was going a bit off of this paper. Unfortunately, monitoring fire-recovery is a whole different challenge, so this is kinda where our work with the wonder pole and the chrysolepsis experiment come into play bc in a post-fire situation we now know that approx. x% of the the area under the canopy is understory and approx. x% is actually the regrowing vegetation. Which can help with interpreting any signals. Although this might change since agrifolia and valley oak are a bit different from chrysolepsis and we did this 10 years after the fire. So, is there a potential to expand on the work we did to monitor how those percentages change over time after a fire to help with short and long term monitoring of post-fire oak recovery via remote sensing?

So now we are looking to see what type of imagery is available for the park and which has already been processed. They have a good connection with NASA so there's a high potential that they have some pretty useful stuff ready for use. I do know a NASA intern group used MESMA to try to classify vegetation across the park, but the accuracy for oaks was only 50%. Not great. But sounds like a spectral library has already been built. Good thing is they do not expect this project to be complete by the end of summer. They understand it is a complex problem that won't be solved in 12 (now 9) weeks. If I can get the methodology and an experimental framework set up for someone else to pick up later they would be very happy with that.

So, given your experience I'm interested in any ideas, thoughts, or concerns you have about monitoring oaks/conifers given the issue of understory vegetation influencing satellite sensors. So shoot me an email or we can have a zoom call! Or if you know someone else I should talk to pass me along!

Christopher Kibler <kibler@ucsb.edu>
to me
Fri, Jul 17, 11:06 AM

Howdy,

Here are my thoughts:

- LiDAR is probably your best bet if there's LiDAR data. That will be very useful for distinguishing trees from shrubs. Has NPS commissioned LiDAR for this area? The publicly-available topographic LiDAR won't have a high enough resolution to distinguish individual trees. You'll need a dedicated data set.
- I don't think the skeletons will be as much of an issue as they are with Berberidifolia and Chrysolepis. Agrifolia has more of a tree structure, and I've always thought that skeletons are more of an issue with shrubby plants that resprout from the burl.
- MESMA species classification is hard and often not great. I would avoid that route. It takes a lot of calibration and validation, and even then the classifications vastly simplify species cover.
- Phenology can help you here. Agrifolia is evergreen, while a lot of understory species are drought deciduous. So I would pick imagery from the driest part of the year.
- Agrifolia also grows in topographic convergences and other wet spots on the landscape. You might be able to leverage that information to filter out some of the more unlikely classifications.
- If I were doing this (without LiDAR), I would probably do a time series of dNBR using imagery from the driest part of the year. dNBR will be less sensitive to pixels that don't have a lot of green vegetation. It would be confused by other evergreen species, though. But I think that would probably be your best bet for an achievable analysis given the limitations.

I hope this helps. Let me know if you have any other questions.

Chris

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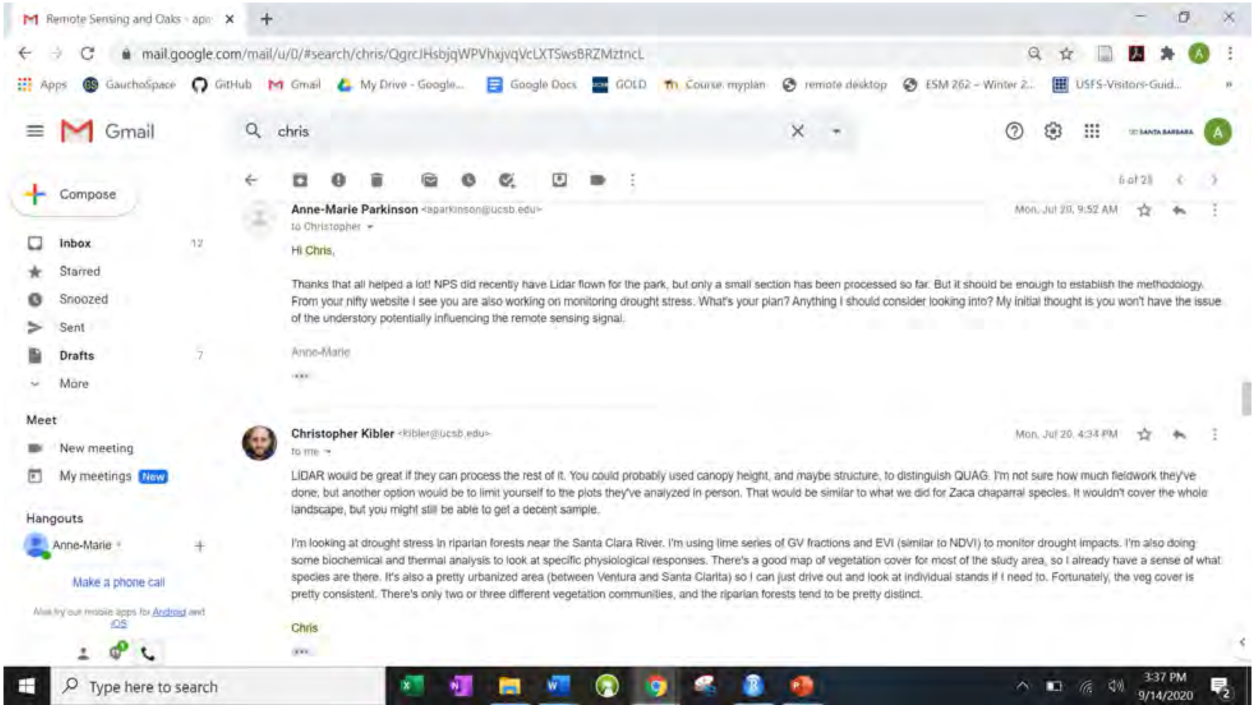
Christopher Kibler
PhD Student
Department of Geography



Anne-Marie Parkinson <aparkinson@ucsb.edu> — Mon, Jul 20, 9:52 AM
to Christopher

Hi Chris,

Thanks that all helped a lot! NPS did recently have Lidar flown for the park, but only a small section has been processed so far. But it should be enough to establish the methodology. From your nifty website I see you are also working on monitoring drought stress. What's your plan? Anything I should consider looking into? My initial thought is you won't have the issue of the understory potentially influencing the remote sensing signal.

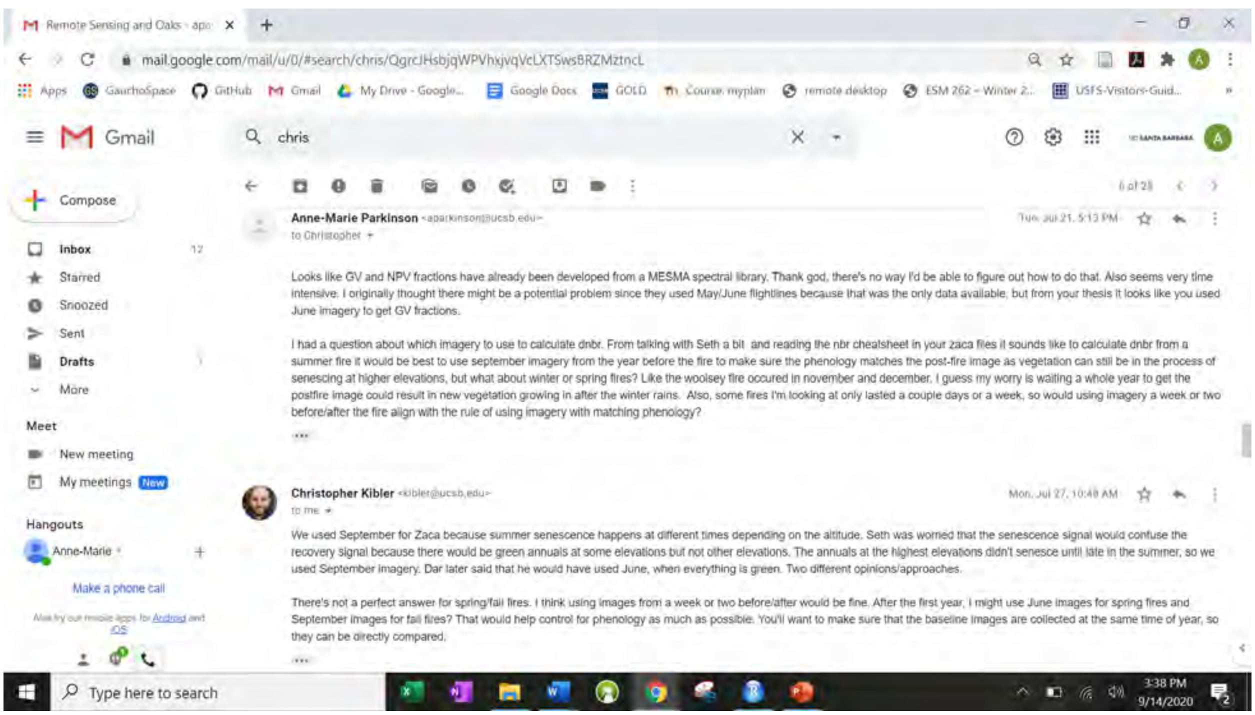
Anne-Marie

Christopher Kibler <kibler@ucsb.edu> — Mon, Jul 20, 4:34 PM
to me

LIDAR would be great if they can process the rest of it. You could probably used canopy height, and maybe structure, to distinguish QUAG. I'm not sure how much fieldwork they've done, but another option would be to limit yourself to the plots they've analyzed in person. That would be similar to what we did for Zaca chaparral species. It wouldn't cover the whole landscape, but you might still be able to get a decent sample.

I'm looking at drought stress in riparian forests near the Santa Clara River. I'm using time series of GV fractions and EVI (similar to NDVI) to monitor drought impacts. I'm also doing some biochemical and thermal analysis to look at specific physiological responses. There's a good map of vegetation cover for most of the study area, so I already have a sense of what species are there. It's also a pretty urbanized area (between Ventura and Santa Clarita) so I can just drive out and look at individual stands if I need to. Fortunately, the veg cover is pretty consistent. There's only two or three different vegetation communities, and the riparian forests tend to be pretty distinct.

Chris



Anne-Marie Parkinson <aparkinson@ucsb.edu> — Tue, Jul 21, 5:13 PM
to Christopher

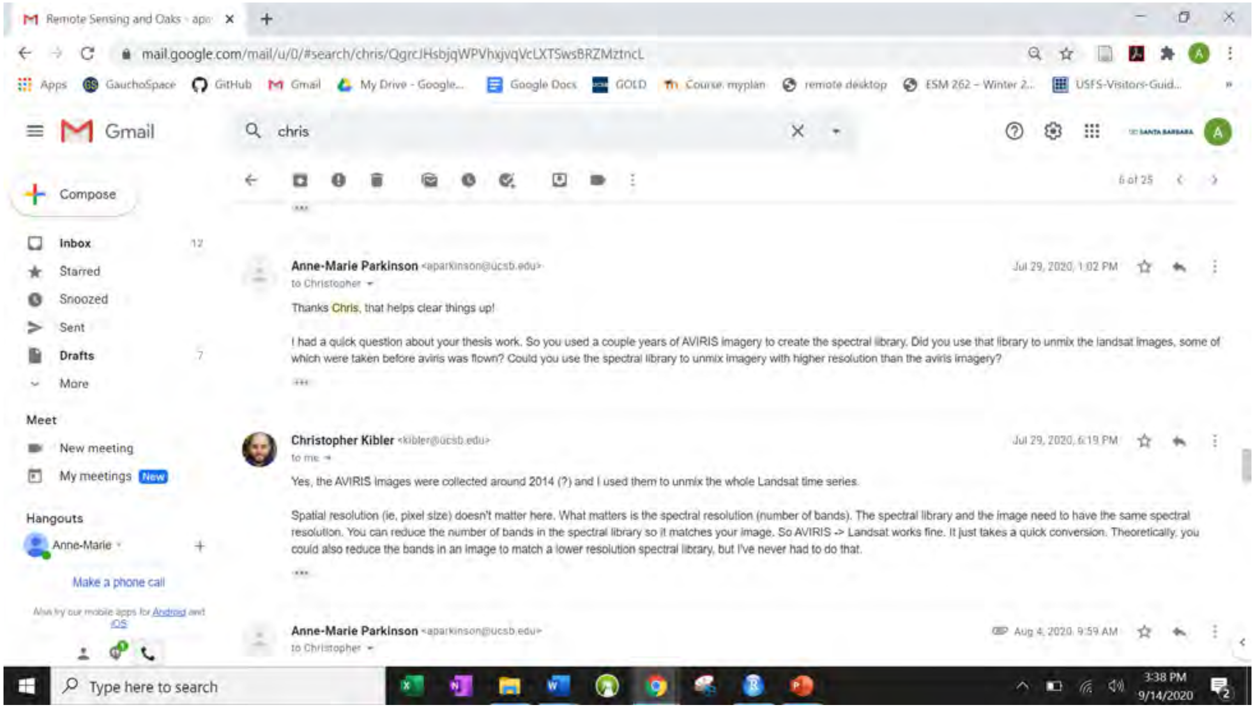
Looks like GV and NPV fractions have already been developed from a MESMA spectral library. Thank god, there's no way I'd be able to figure out how to do that. Also seems very time intensive. I originally thought there might be a potential problem since they used May/June flightlines because that was the only data available, but from your thesis it looks like you used June imagery to get GV fractions.

I had a question about which imagery to use to calculate dnbr. From talking with Seth a bit and reading the nbr cheatsheet in your zaca files it sounds like to calculate dnbr from a summer fire it would be best to use september imagery from the year before the fire to make sure the phenology matches the post-fire image as vegetation can still be in the process of senescing at higher elevations, but what about winter or spring fires? Like the woolsey fire occured in november and december. I guess my worry is waiting a whole year to get the postfire image could result in new vegetation growing in after the winter rains. Also, some fires I'm looking at only lasted a couple days or a week, so would using imagery a week or two before/after the fire align with the rule of using imagery with matching phenology?

Christopher Kibler <kibler@ucsb.edu> — Mon, Jul 27, 10:48 AM
to me

We used September for Zaca because summer senescence happens at different times depending on the altitude. Seth was worried that the senescence signal would confuse the recovery signal because there would be green annuals at some elevations but not other elevations. The annuals at the highest elevations didn't senesce until late in the summer, so we used September imagery. Dar later said that he would have used June, when everything is green. Two different opinions/approaches.

There's not a perfect answer for spring/fall fires. I think using images from a week or two before/after would be fine. After the first year, I might use June images for spring fires and September images for fall fires? That would help control for phenology as much as possible. You'll want to make sure that the baseline images are collected at the same time of year, so they can be directly compared.


Remote Sensing and Oaks - apa
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Inbox 12
Starred
Snoozed
Sent
Drafts 7
More
Meet
New meeting
My meetings New
Hangouts
Anne-Marie
Make a phone call
6 of 25
Anne-Marie Parkinson <aparkinson@ucsb.edu>
to Christopher
Jul 29, 2020, 1:02 PM
Thanks Chris, that helps clear things up!
I had a quick question about your thesis work. So you used a couple years of AVIRIS imagery to create the spectral library. Did you use that library to unmix the landsat images, some of which were taken before aviris was flown? Could you use the spectral library to unmix imagery with higher resolution than the aviris imagery?
Christopher Kibler <kibler@ucsb.edu>
to me
Jul 29, 2020, 6:19 PM
Yes, the AVIRIS images were collected around 2014 (?) and I used them to unmix the whole Landsat time series.
Spatial resolution (ie, pixel size) doesn't matter here. What matters is the spectral resolution (number of bands). The spectral library and the image need to have the same spectral resolution. You can reduce the number of bands in the spectral library so it matches your image. So AVIRIS -> Landsat works fine. It just takes a quick conversion. Theoretically, you could also reduce the bands in an image to match a lower resolution spectral library, but I've never had to do that.
Anne-Marie Parkinson <aparkinson@ucsb.edu>
to Christopher
Aug 4, 2020, 9:59 AM
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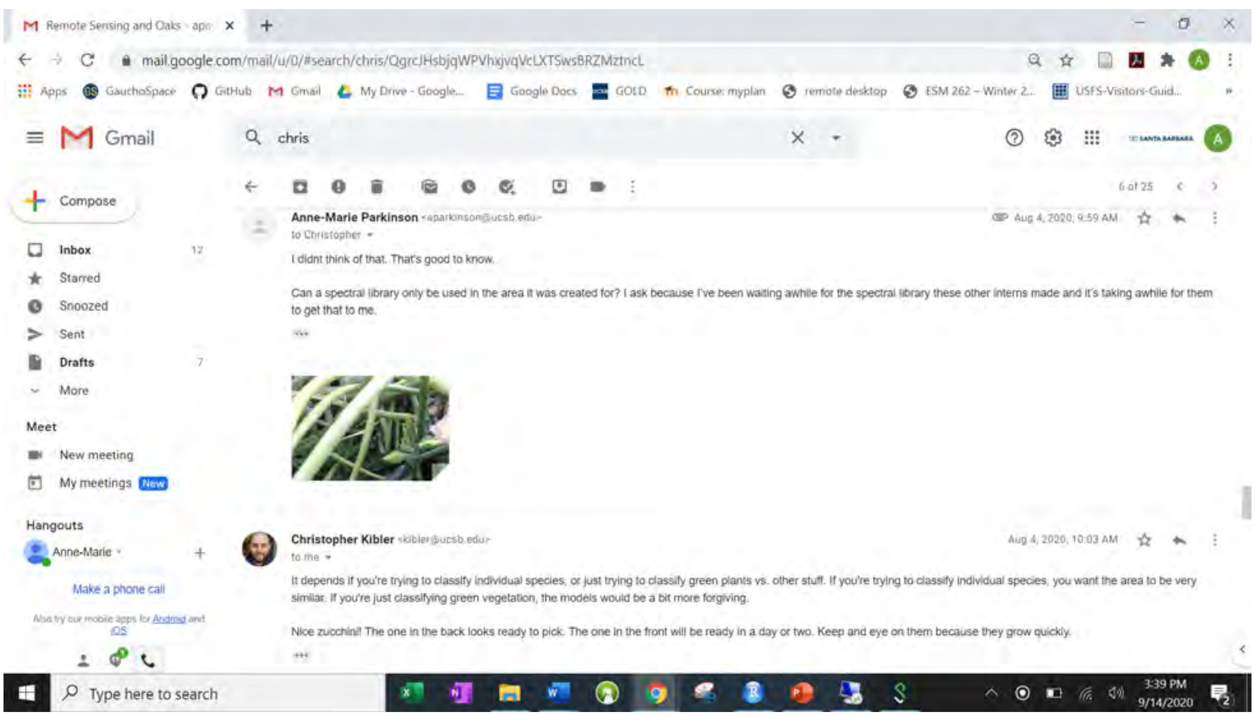
9/14/2020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chris
Compose
6 of 25
Anne-Marie Parkinson <aparkinson@ucsb.edu>
to Christopher
Aug 4, 2020, 9:59 AM
I didnt think of that. That's good to know.
Can a spectral library only be used in the area it was created for? I ask because I've been waiting awhile for the spectral library these other interns made and it's taking awhile for them to get that to me.
Christopher Kibler <kibler@ucsb.edu>
to me
Aug 4, 2020, 10:03 AM
It depends if you're trying to classify individual species, or just trying to classify green plants vs. other stuff. If you're trying to classify individual species, you want the area to be very similar. If you're just classifying green vegetation, the models would be a bit more forgiving.
Nice zucchini! The one in the back looks ready to pick. The one in the front will be ready in a day or two. Keep and eye on them because they grow quickly.
Type here to search
3:39 PM
9/14/2020