Quantifying Post-Wildfire Vegetation Regrowth in California since Landsat 5

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ABSTRACT

The relationship between wildfire and vegetation regrowth in California has important implications for policy and conservation. Despite this, few previous studies have investigated fire and regrowth at a statewide level or across broad time scales and vegetation classes. Consequently, there is no standardized measure to compare response to fire over time in different ecological communities, leaving an important gap in our understanding of how California will respond to increasing drought and fire frequency. To investigate this relationship, I combined the power of emerging tools in data science implemented in Google Earth Engine (GEE) with freely available CALVEG data and Landsat 5 and 8 normalized difference vegetation index (NDVI) time series to examine the effects of fire frequency on vegetation regrowth for nine vegetation categories across California. The nine vegetation categories were chosen to capture the statewide heterogeneity and included oak, conifer, hardwood, desert, herbaceous, shrub, mixed forest, other, and agriculture. Through the use of cloud computing I was able to simultaneously analyze every pixel in California that has burned since 1984, using NDVI as a measure of vegetation greenness and regrowth. I found that mean NDVI was significantly lower in burned pixels than unburned pixels in 4 of the 9 vegetation categories, and NDVI also decreased as fire frequency increased in 6 of the 9 vegetation categories. I concluded that fire has a significant effect on vegetation regrowth in California, but to varying magnitude and direction across the different ecosystems.

KEYWORDS

Remote sensing, Google Earth Engine (GEE), NDVI, fire frequency, California ecosystems

INTRODUCTION

Although the full effect of climate change on global fire behavior has yet to be seen, an emerging consensus on fire in the Western United States is taking shape, with quantitative studies indicating that climate change has contributed to the increase in frequency and severity of fires throughout California (Westerling et al. 2006, Miller et al. 2008, van Mantgem et al. 2013, Dennison et al. 2014, Arnold et al. 2014). Although high severity fire regimes are sometimes a natural feature of the landscape, very severe fires can inhibit seedling regeneration, alter species composition, and allow the establishment of invasive species (Kozlowski 2012, Stephens et al. 2013). High fire frequency similarly causes varying effects on the landscape, ranging from increased heterogeneity to decreased fire severity (Trabaud and Galtié 1996). Furthermore, factors such as grazing, clear-cutting, pest outbreaks, climate change, and fire exclusion have created fire regimes never before seen in the past (Wright 1974). This deviation from historic baselines makes understanding contemporary patterns of post-fire vegetation regrowth even more important for predicting future landscape response to climate shifts.

Looking more closely at the interaction of vegetation and fire reveals complex relationships between species composition, fire regime type, and the measure of vegetation applied. Many previous studies use satellite derived change in normalized difference vegetation index (NDVI) as a proxy for vegetation regrowth and have shown that aspect, elevation, and fire frequency have the greatest effect on NDVI (Díaz-Delgado et al. 2003, Casady et al. 2009, Huang et al. 2013, Paci et al. 2015, Meng et al. 2015). In some cases, fire frequency inversely affects vegetation mortality by decreasing fuel load, subsequently leading to lower intensity fires (Crotteau et al. 2013, Stephens et al. 2013). Additionally, many landscapes reset to earlier stages of succession after burning, for example, woody plant and herbaceous species may convert back to shrubland, or fire resistant seedlings lying dormant in the soil may dominate the new landscape and push out old species (D'Antonio and Vitousek 1992, Sugihara 2006, Moreira et al. 2011, Crotteau et al. 2013).

This study builds on previous research, and seeks to understand patterns of post-fire vegetation regrowth at a statewide scale, at a resolution that has only recently been made possible by advances in computing power. Specifically, this study aims to provide land managers with crucial information on the ways fire affects post-fire regrowth, so that they may better understand California's changing ecosystem. I will do this by using Google Earth Engine (GEE) to automate the analysis of the effect of fire frequency on statewide vegetation regrowth, therefore providing a blueprint for future studies across varying spatial and temporal scales. Furthermore, my dataset encompasses all fires in California, so the results should accurately represent the extent of the entire state, and allow me to identify large scale trends. Ultimately, my study will identify patterns that cannot be seen in other fine scale studies that require highly dimensional studies of the landscape. To my knowledge, few others have characterized vegetation regrowth at such a broad spatial and temporal scale.

This research will quantify the relationship between fire frequency and post-fire vegetation regrowth for every fire in California since 1984 (N=1771 *number of fires). Using NDVI as a measure of vegetation condition, I will identify if (a) burned pixels have lower mean NDVI values as compared to unburned pixels across each vegetation type and (b) if mean NDVI varies with fire frequency across each vegetation type. I hypothesize that higher fire frequency will lead to lower post-fire vegetation regrowth than low and intermediate frequencies, and that burned pixels will have lower mean NDVI than unburned pixels. This information on post-fire vegetation trajectory will be invaluable for land managers to avoid economic losses from fire.

METHODS

Study site

This study site includes all areas in California, USA (36.7783° N, 119.4179° W), burned and unburned, that intersect vegetation types that have burned at least once from 1984 to 2015. This intersection overlays all ten ecoregions that make up California, although some regions have burned more than others (Figure 1). Dry and windy forest habitats in the south and east tended to burn more than the Central Valley and coastal areas (Flannigan and Wotton 2001). Unsurprisingly, these forested areas also have very expansive and different ranges of vegetation, fire regimes, and management styles (Syphard et al. 2007). Though it is difficult to characterize California and its vegetation as a whole, I used 9 aggregated vegetation categories ranging from oak to agriculture (Figure A1) (Figure A2). This allowed me to reduce pre-processing work, while still capturing the statewide heterogeneity. Combined with fire frequency history, vegetation regrowth trajectory will provide an interesting insight into overall fire trends in California.

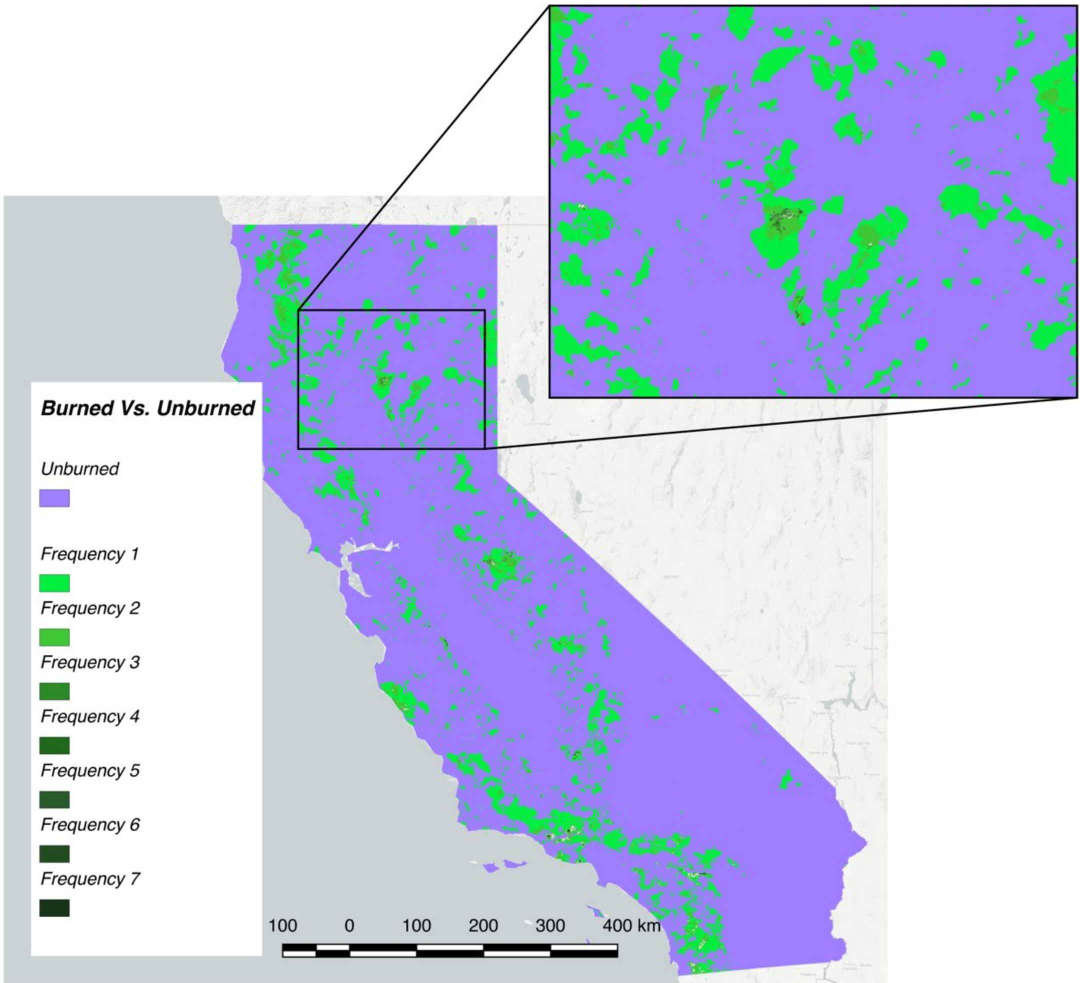

Figure 1. Map of study site showing unburned area and fire frequency. Differences in fire frequency can be seen in the magnified map in green. Data was downloaded from The California Department of Forestry and Fire Protection's CALFIRE Fire and Resource Assessment Program (FRAP).

Data collection

Data and software description

To determine how fire frequency affected vegetation regrowth across a range of vegetation types I used a program called Google Earth Engine (GEE) (Google Earth Engine Team 2016). GEE harnesses cloud computing in a JavaScript API to allow users to host, process, and analyze planetary scale geospatial data. Within GEE, I used four detailed 30m resolution spatial datasets for my analysis: Landsat 5 annual NDVI composite, Landsat 8 annual NDVI composite, CALVEG statewide vegetation raster, and a cumulative FRAP fire frequency raster of all fires that occurred between 1984-2015 (U.S Geological Survey 1984, 2013, USDA-Forest Service 2004, California Department of Forestry and Fire Protection 2015).

The Landsat 5 and 8 annual NDVI composites were created using Standard Terrain Corrected scenes and top-of-atmosphere (TOA) reflectance. NDVI is an index used to estimate biomass and net primary productivity and is generated from the Near-IR and Red bands of each tile (NIR – Red) / (NIR + Red). The index has values ranging from -1 to 1, with 1 being dense vegetation, 0 being bare ground, and negative values being snow or water. Composites are then created from all the scenes in each annual period, and all the images from each year are included in the composite, with the most recent pixel as the composite value (Xie et al. 2008, Google Earth Engine Team 2016). After merging the composites, I filtered for the dates of my study period: January 1, 1984 – December 31, 2015 (Figure 2.A). The cumulative fire frequency raster ranges from pixels that have burned 0 times to pixels that have burned 7 times, and represents the cumulative number of fires across the whole 28-year study period (Figure 2.B). I also filtered the 65 vegetation types in the CALVEG raster down to 9 vegetation categories which include oak, conifer, desert, agriculture, hardwood, herbaceous, mixed forest, other, and shrub (Figure 2.C.1) (Table 1).

One limitation of NDVI is that different processes can lead to the same observation. For example, if a grassland is converted to shrubland after burning, NDVI may remain the same since an equivalent amount of productive biomass is still present (Kozlowski 2012, Meng et al. 2014). As with any remotely sensed index, NDVI does not perfectly align with plant health, species composition, or productivity, so it can be difficult to capture the dynamic nature of vegetation. Although previous studies using satellite derived measures of vegetation after fire are important, they are limited to small study areas, short time spans, and specific vegetation classes.

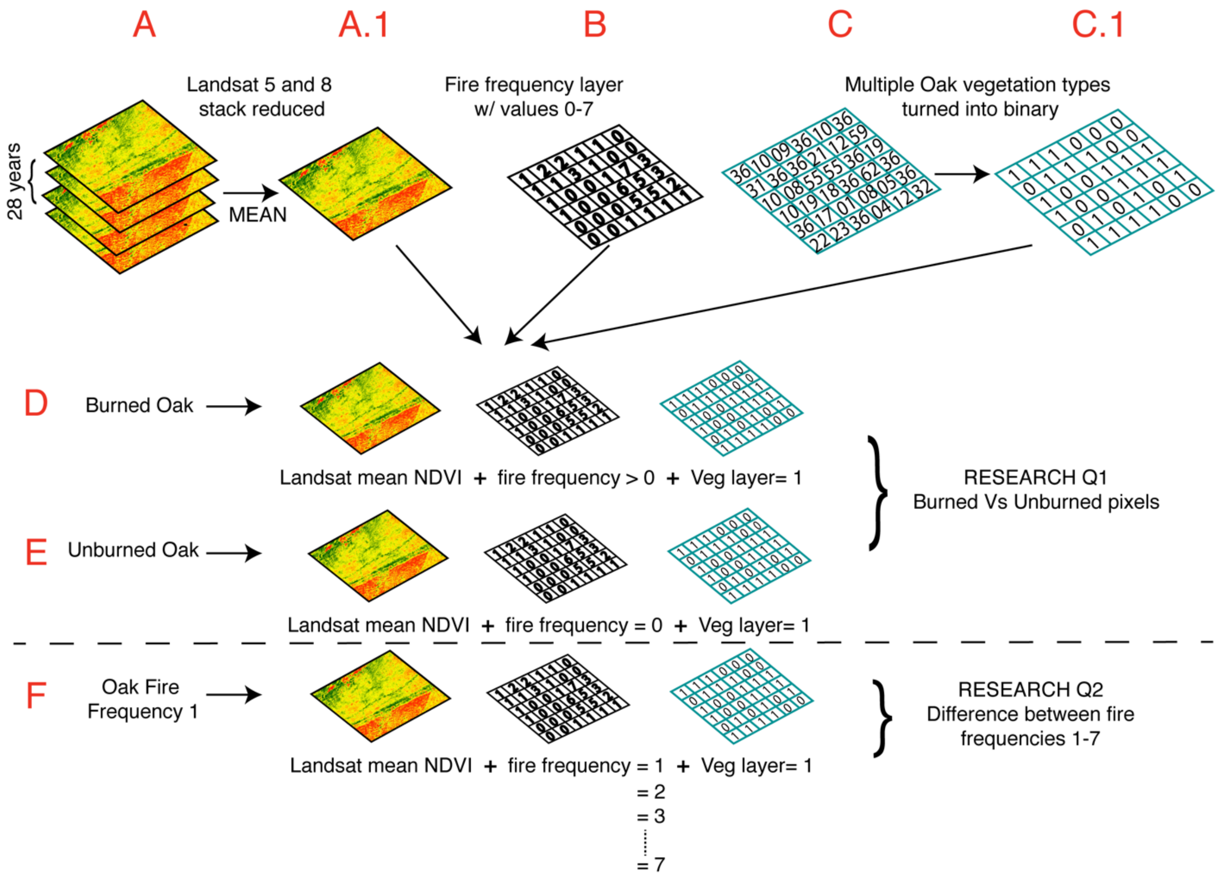

Figure 2. Workflow diagram for the oak vegetation category. This same process was repeated for each of the 9 vegetation categories, with alterations to step "C" to reflect the different codes for each vegetation types. Each square represents a raster data layer covering all of California.

Table 1. Vegetation types contained in 9 vegetation categories. Some oak vegetation types appear both in the hardwood and mixed forest vegetation categories, in order to separate out the effects of fire on oak. All vegetation types have burned at least once since 1984. Data was provided through the U.S. Forest Service CALVEG GIS repository

Category Name	Vegetation Types
Oak	Blue Oak Woodland, Coastal Oak Woodland, Valley Oak Woodland, Montane Hardwood, Blue Oak-Foothill Pine
Conifer	Closed-Cone Pine-Cypress, Douglas Fir, Eastside Pine, Jeffrey Pine, Juniper Lodgepole Pine, Pinyon-Juniper, Ponderosa Pine, Redwood, Red Fir, Subalpine Conifer, Sierran Mixed Conifer, White Fir, Undetermined Conifer
Desert	Desert Riparian, Joshua Tree, Alkali Desert Scrub, Desert Scrub, Desert Succulent Shrub, Desert Wash
Agriculture	Evergreen Orchard, Palm Oasis, Deciduous Orchard, Dryland Grain Crops Irrigated Grain Crops, Irrigated Row and Field Crops, Irrigated Hayfield, Pasture, Rice, Cropland, Orchard - Vineyard, Vineyard
Hardwood	Montane Hardwood, Undetermined Hardwood, Eucalyptus
Herbaceous	Annual Grassland, Perennial Grassland
Mixed Forest	Blue Oak-Foothill Pine, Klamath Mixed Conifer, Montane Hardwood-Conifer
Other	Fresh Emergent Wetland, Saline Emergent Wetland, Wet Meadow,Barren Estuarine, Lacustrine, Riverine, Urban, Water, Marsh, Montane Riparian Valley Foothill Riparian
Shrub	Alpine-Dwarf Shrub, Aspen, Bitterbrush, Chamise-Redshank Chaparral, Coastal Scrub, Low Sage, Mixed Chaparral, Montane Chaparral, Sagebrush, Undetermined Shrub

Extracting mean NDVI values for burned pixels, unburned pixels, and fire frequencies 1-7

First, using the vegetation layer (Figure 2.C), I created 9 separate raster layers that classify each vegetation category of interest into a binary format of presence or absence (Figure 2.C.1). I then overlayed the mean NDVI layer (Figure 2.A.1), the fire frequency layer (Figure 2.B), and the binary layer (Figure 2.C.1). This associates each pixel with a mean NDVI value, a fire frequency number, and a binary value. I then queried the mean NDVI for burned pixels by selecting for fire frequency values over 0 (Figure 2.D), unburned pixels by selecting for fire frequency equal to 0 (Figure 2.E), and for each fire frequency by selecting for values 1-7 (Figure 2.F). I repeated this for all 9 vegetation categories, and then used reducers to get values for mean, standard deviation, sample size, percentiles, fixed histograms, and variance. By using reducers to calculate summary statistics I was able to export out the information on the 500,000,000 pixels more efficiently, but consequently had to compromise the resolution of my data.

Data Analysis

To analyze how wildfire has affected mean NDVI across California, I used a combination of analysis of variance (ANOVA), two sample *t*-tests, and linear regression.

To investigate my first sub-question, I used the "BSDA" package implemented in R Studio to perform a two-sample *t*-test on the summary data extracted in GEE (Arnholt 2012, RStudio Team 2016) . After checking for normality and homogeneity of variances with a visual inspection of the data, I used burned state (burned/unburned) as the independent variable and mean NDVI as the dependent variable. A *t*-test was performed on each vegetation category separately.

To examine my second sub-question, I used a one-way ANOVA for each vegetation type with fire frequency as the independent variable and mean NDVI as the dependent variable. After checking that the assumptions of normally distributed residuals and homogeneity of variances with a visual inspection of the data, I used the "rpsychi" and "asbio" packages to perform the one-way ANOVAs and subsequent post-hoc Tukey tests (Yasuyuki 2012, Aho 2016), using the ANOVA to test whether or not the mean NDVI values are significantly different overall, and the Tukey tests to determine which pairwise comparisons were different. Finally, to quantify the overall trend in fire frequency, I regressed mean NDVI on fire frequency to get a slope and *p*-value using the "lm" function in R studio (RStudio Team 2016).

Although the use of summary data in statistical testing is not ideal, this method was necessary due to the large size of our raw data (Larson 1992). The full summary data used in all statistical testing is provided below along with the standardized coefficients of variation, since the condition of homogeneity of variance is not fully met (Table 2) (Table 3). Specifically, in the frequency data, although statistically significant, this may overestimate the biological significance since small differences in means are often significant owing to the extremely large sample sizes (Lix et al. 1996). Although my data did not meet the assumptions of homogeneity of variances, the exact magnitude that constitutes a violation of homogeneity is disputed, and therefore I decided to continue with parametric statistics.

Table 2. Table of summary statistics for burned and unburned pixels for each vegetation category. The coefficient of variation, mean NDVI, sample size, and standard deviation are included so that the biological significance can be assessed by the reader.

		Burn Condition	
		Burned	Unburned
Oak	Coefficient of Variation	0.34744	0.33585
	Mean NDVI	0.29363	0.29550
	Sample Size	9304372.45	42207075.27
	Standard Deviation	0.10201826	0.09924296
Conifer	Coefficient of Variation	0.36291	0.40802
	Mean NDVI	0.29927	0.29496
	Sample Size	15639459.73	85568471.87
	Standard Deviation	0.10860954	0.12034903
Desert	Coefficient of Variation	0.35858	0.42238
	Mean NDVI	0.13189	0.08325
	Sample Size	1496104.42	124813034.01
	Standard Deviation	0.04729268	0.03516144
Agriculture	Coefficient of Variation	0.38747	0.44080
	Mean NDVI	0.25275	0.18921
	Sample Size	605693.41	63170168.00
	Standard Deviation	0.09793394	0.08340494
Hardwood	Coefficient of Variation	0.35396	0.32953
	Mean NDVI	0.31652	0.33328
	Sample Size	4651479.80	17543112.43
	Standard Deviation	0.11203459	0.10982577
Herbaceous	Coefficient of Variation	0.33965	0.31281
	Mean NDVI	0.19561	0.20266
	Sample Size	8083290.35	61199631.22
	Standard Deviation	0.06643737	0.06339475
Mixed Forest	Coefficient of Variation	0.32998	0.30987
	Mean NDVI	0.34104	0.36091
	Sample Size	5419853.65	21897386.67
	Standard Deviation	0.11253768	0.11183291
Other	Coefficient of Variation	0.51028	1.20354
	Mean NDVI	0.20903	0.10984
	Sample Size	2109063.96	57289946.21
	Standard Deviation	0.10666569	0.13219651
Shrub	Coefficient of Variation	0.40275	0.53571
	Mean NDVI	0.23863	0.19203
	Sample Size	27857561.64	57275601.64
	Standard Deviation	0.09610747	0.10287384

Table 3. Table of summary statistics for each fire frequency for each vegetation category. The coefficient of variation, mean NDVI, sample size, and standard deviation are included. Blank spaces are present since some vegetation categories had a maximum fire frequency of less than seven.

		Fire Frequency						
		1	2	3	4	5	6	7
Oak	Coefficient of Variation	0.34451	0.36237	0.36687	0.30359	0.38940	0.33083	
	Mean NDVI	0.29415	0.29568	0.26055	0.25382	0.24151	0.12292	
	Sample Size	8002519.18	1111465.27	174378.00	14121.00	1859.00	30.00	
	Standard Deviation	0.10133547	0.10714523	0.09558871	0.07705546	0.09404284	0.04066425	
Conifer	Coefficient of Variation	0.36205	0.37199	0.30670	0.30205	0.10484		
	Mean NDVI	0.29943	0.29898	0.28197	0.25715	0.22419		
	Sample Size	14211343.65	1793613.98	86824.00	3686.00	38.00		
	Standard Deviation	0.10840630	0.11121989	0.08648033	0.07767154	0.02350498		
Desert	Coefficient of Variation	0.34123	0.43490	0.43589	0.62517	0.57081	0.42048	
	Mean NDVI	0.13088	0.14121	0.14728	0.11659	0.12557	0.14087	
	Sample Size	1322349.51	135099.91	18982.00	13564.00	4710.00	1489.00	
	Standard Deviation	0.04466173	0.06141192	0.06419788	0.07288737	0.07167393	0.05923462	
Agriculture	Coefficient of Variation	0.39035	0.34570	0.27911	0.33528	0.11924	0.10110	
	Mean NDVI	0.24927	0.28566	0.30580	0.21945	0.17534	0.17109	
	Sample Size	550372.82	47846.59	7011.00	133.00	127.00	203.00	
	Standard Deviation	0.09730342	0.09875218	0.08535276	0.07357964	0.02090802	0.01729748	
Hardwood	Coefficient of Variation	0.34975	0.37768	0.38915	0.32412	0.40334	0.33827	
	Mean NDVI	0.31763	0.31342	0.26886	0.24645	0.21741	0.12369	
	Sample Size	4028784.14	568503.66	50503.00	2394.00	1271.00	24.00	
	Standard Deviation	0.11108822	0.11837164	0.10462646	0.07987981	0.08769182	0.04184158	
Herbaceous	Coefficient of Variation	0.34481	0.31782	0.25981	0.29450	0.46982	0.44457	
	Mean NDVI	0.19387	0.20488	0.20823	0.18680	0.14607	0.13279	
	Sample Size	6783121.15	1041798.29	219963.92	30659.00	6512.00	1134.00	
	Standard Deviation	0.06684955	0.06511532	0.05409938	0.05501202	0.06862517	0.05903641	
Mixed Forest	Coefficient of Variation	0.32545	0.34638	0.41633	0.21510	0.32112		
	Mean NDVI	0.34359	0.33073	0.25586	0.28170	0.23742		
	Sample Size	4613716.72	760025.93	45378.00	692.00	41.00		
	Standard Deviation	0.11181986	0.11456112	0.10652417	0.06059349	0.07624024		
Other	Coefficient of Variation	0.51640	0.46037	0.38040	0.37273	0.40357	0.33316	
	Mean NDVI	0.20662	0.23095	0.21787	0.21630	0.17316	0.17675	
	Sample Size	1885351.31	199650.88	24089.77	1768.00	369.00	174.00	
	Standard Deviation	0.10669549	0.10632325	0.08287654	0.08062297	0.06988404	0.05888474	
Shrub	Coefficient of Variation	0.40301	0.40370	0.36274	0.34179	0.34196	0.23754	0.09134
	Mean NDVI	0.23783	0.24762	0.22096	0.20863	0.20074	0.18614	0.18119
	Sample Size	23246367.09	3808613.57	692873.20	97059.78	11743.00	842.00	63.00
	Standard Deviation	0.09584840	0.09996425	0.08014976	0.07130788	0.06864446	0.04421762	0.01654995

RESULTS

Mean NDVI- burned and unburned Pixels

A comparison between burned and unburned NDVI values across the 9 vegetation categories suggests that the effect of burning depended on vegetation category. Burned pixels had a significantly lower mean NDVI than unburned pixels in 4 of the 9 vegetation categories, which included oak, hardwood, herbaceous, and mixed forest. In the other 5 vegetation categories which included conifer, shrub, desert, other, and agriculture, the burned pixels had a significantly higher mean NDVI than the unburned pixels (Table 2). Overall, fire had a statistically significant effect on all vegetation categories, but the magnitude and direction of that effect varied across the categories (Figure 3).

Table 2. Results of the *t*-tests for each vegetation category. Statistically significant p-values at alpha = 0.05 are indicated with an asterisk

	Vegetation Category								
	Oak	Conifer	Desert	Agriculture	Hardwood	Herbaceous	Mixed Forest	Other	Shrub
P-Value	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*
T-Statistic	-50.873	142.000	1253.900	503.190	-288.090	-285.360	-368.430	1313.900	2050.700

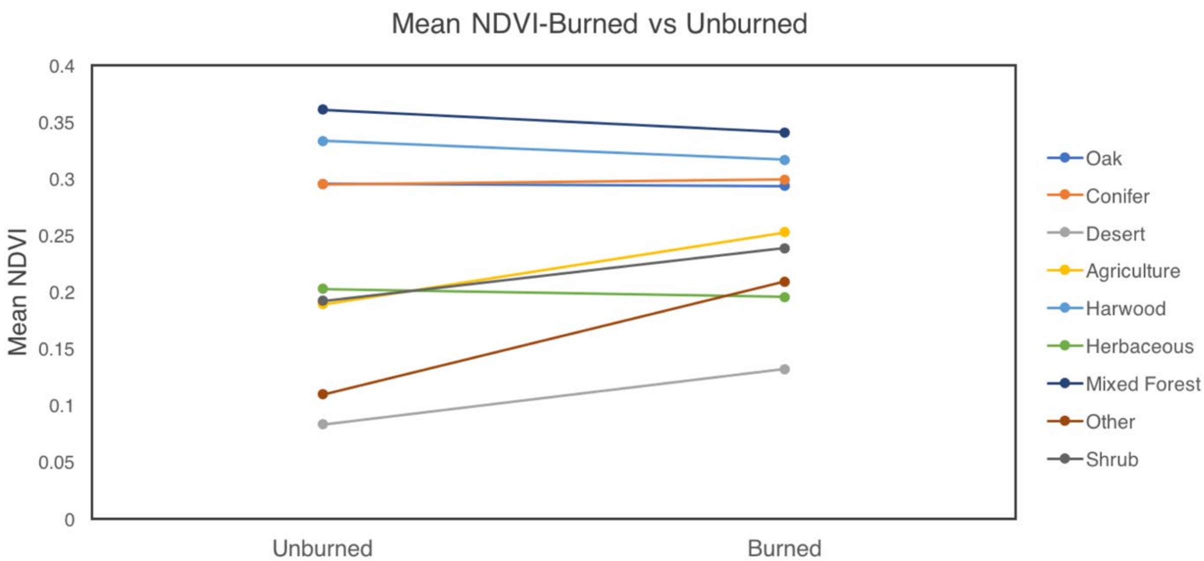

Figure 3. Graph showing the trend in mean NDVI between burned and unburned pixels. The oak, hardwood, herbaceous, and mixed forest vegetation categories exhibited lower mean NDVI values in burned pixels as compared to unburned pixels. The conifer, shrub, desert, other, and agriculture vegetation category showed the opposite relationship.

Mean NDVI by fire frequency

An examination of mean NDVI by fire frequency revealed similar trends as in the previous analysis. The *p*-values and post-hoc results showed that almost all of the pairwise comparisons between each fire frequency were significantly different, with the exception of 10 out of the 131 tests, although this may have been driven by differences in sample size (Table 3) (Figure 4). After regressing mean NDVI on fire frequency, I saw that conifer, oak, hardwood, herbaceous, mixed forest, and shrub decreased significantly as fire frequency increased (Table 4). On the other hand, desert, other, and agriculture showed little to no change in mean NDVI with fire frequency (Figure 5). Interestingly, 6 of the 9 vegetation categories showed an initial increase in mean NDVI in pixels that burned once, and some categories like desert, herbaceous, and shrub continued to show an increase until frequency 3. Conversely, oak and hardwood showed marked decreases in mean NDVI from frequency 5 to 6, with their mean NDVI dropping below that of a desert.

Table 3. Summary of the results of ANOVA for each fire frequency. Statistically significant *p*-values at alpha = 0.05 are indicated with an asterisk. The top portion of the table shows the post-hoc Tukey *p*-values for each pairwise comparison of each fire frequency for all 9 vegetation categories. The bottom portion shows the overall *p*-value and F-statistic for each ANOVA test.

	Tukey P-Values								
	Oak	Conifer	Desert	Agriculture	Hardwood	Herbaceous	Mixed Forest	Other	Shrub
Frequency 1 Vs. Frequency 2	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*
Frequency 1 Vs. Frequency 3	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*
Frequency 1 Vs. Frequency 4	0.0000*	0.0000*	0.0000*	0.0054*	0.0000*	0.0000*	0.0000	0.0017*	0.0000*
Frequency 1 Vs. Frequency 5	0.0000*	0.0002*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000	0.0000*	0.0000*
Frequency 1 Vs. Frequency 6	0.0000*		0.0000*	0.0000*	0.0000*	0.0000*		0.0028*	0.0000*
Frequency 1 Vs. Frequency 7									0.0001*
Frequency 2 Vs. Frequency 3	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*
Frequency 2 Vs. Frequency 4	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*
Frequency 2 Vs. Frequency 5	0.0000*	0.0002*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*
Frequency 2 Vs. Frequency 6	0.0000*		0.9998	0.0000*	0.0000*	0.0000*		0.0000*	0.0000*
Frequency 2 Vs. Frequency 7									0.0000*
Frequency 3 Vs. Frequency 4	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.9914	0.0000*
Frequency 3 Vs. Frequency 5	0.0000*	0.0091*	0.0000*	0.0000*	0.0000*	0.0000*	0.8307	0.0000*	0.0000*
Frequency 3 Vs. Frequency 6	0.0000*		0.0000*	0.0000*	0.0000*	0.0000*		0.0000*	0.0000*
Frequency 3 Vs. Frequency 7									0.0173*
Frequency 4 Vs. Frequency 5	0.0000*	0.3387	0.0000*	0.0034*	0.0000*	0.0000*	0.1007	0.0000*	0.0000*
Frequency 4 Vs. Frequency 6	0.0000*		0.0000*	0.0000*	0.0000*	0.0000*		0.0000*	0.0000*
Frequency 4 Vs. Frequency 7									0.2592
Frequency 5 Vs. Frequency 6	0.0000*		0.0000*	0.9989	0.007*	0.0000*		0.9991	0.0004*
Frequency 5 Vs. Frequency 7									0.6743
Frequency 6 Vs. Frequency 7									0.9997
Overall P-value	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*
F-Statistic	4350.4190	704.3340	1893.3870	1701.2530	2398.9590	7645.3190	8797.8910	1935.8100	11682.0980

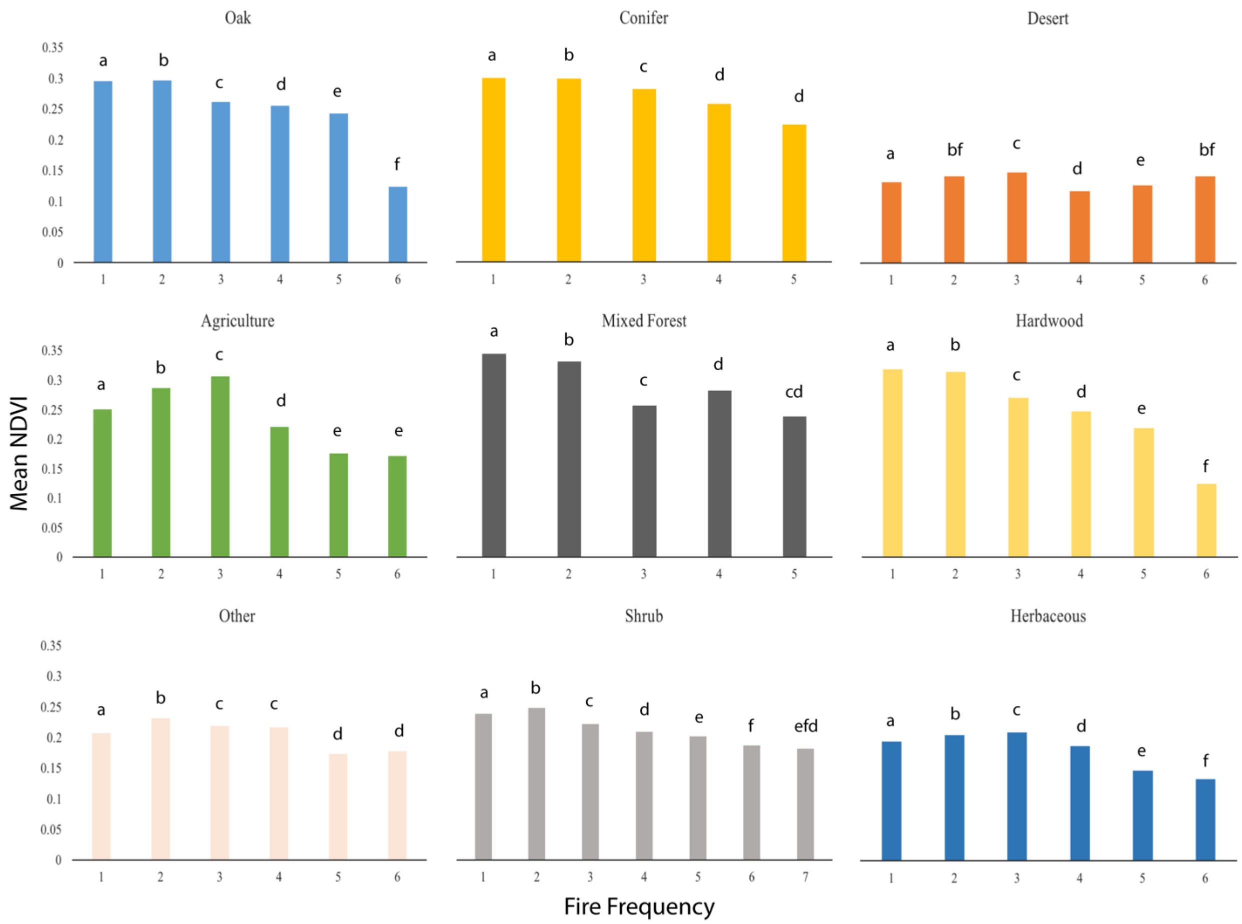

Figure 4. Bar graphs illustrating the relationship between NDVI and fire frequency. Results from ANOVA largely parallel the results of the linear regression analysis, with desert, shrub, and herbaceous categories exhibiting no change or modest decreases, and oak, conifer, and hardwood exhibiting precipitous declines with increasing fire frequency. Letters indicate significance at alpha = 0.05.

Table 4. Results of the linear regression of mean NDVI on fire frequency. Statistically significant *p*-values significance at alpha = 0.05 are indicated by an asterisk. All slopes are negative but only the oak, conifer, hardwood, mixed forest, and shrub categories had significantly negative slopes.

	Vegetation Category								
	Oak	Conifer	Desert	Agriculture	Hardwood	Herbaceous	Mixed Forest	Other	Shrub
Slope	-0.02930	-0.01923	-0.00079	-0.02309	-0.03657	-0.01438	-0.02614	-0.00927	-0.011182
P-value	0.02729*	0.012755*	0.80782	0.07127	0.00373*	.032679*	.040237*	0.09503	0.000483*

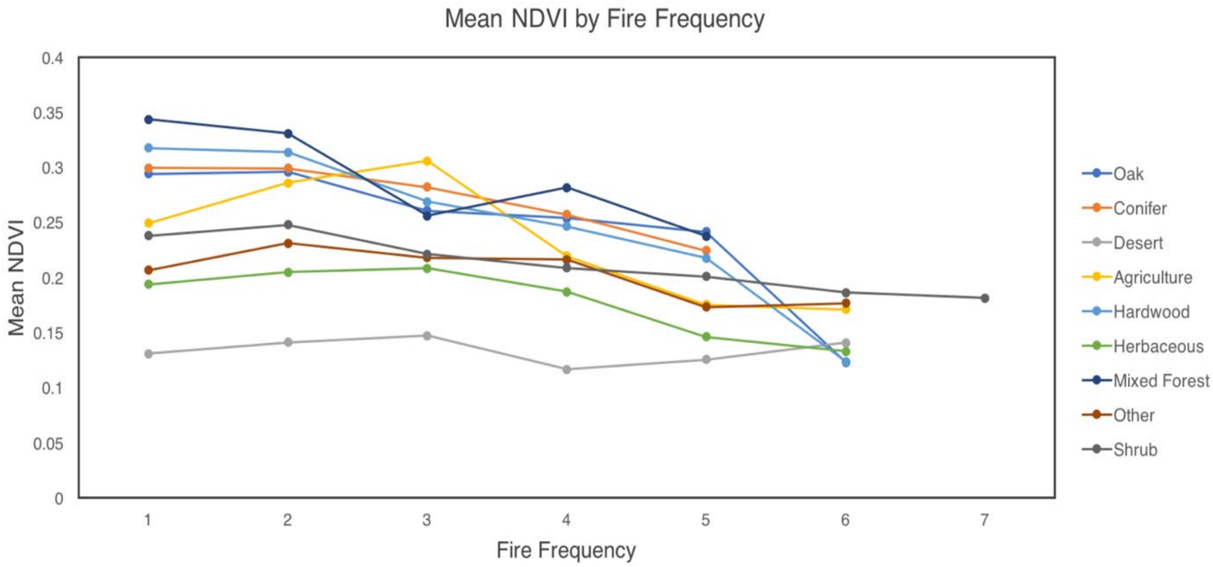

Figure 5. Graph of mean NDVI by fire frequency for each vegetation category. Fire frequency 1 represents pixels that have burned 1 time in the 28-year time period from 1984 to 2015. Some pixels burned up to 7 times.

DISCUSSION

Overall, I successfully used Google Earth Engine to address all of the questions proposed in this study. Despite the limitations of the data posed by the differences in sample size, species composition, and ecosystem type, I was able to discern habitat-specific patterns that are consistent with published observations on how ecosystems respond to fire. I found that mean NDVI was significantly lower in burned pixels than unburned pixels in 4 of the 9 vegetation categories, with the opposite relationship seen in the other 5 categories. In addition, I saw that mean NDVI varied with fire frequency, with NDVI decreasing as fire frequency increased in 6 of the 9 vegetation types. Although my findings are consistent with the results of previous studies performed at smaller spatial and temporal scales, a number of factors make this study novel including the use of fire frequency as opposed to the more commonly used metric of fire severity, implementation of the project in Google Earth Engine, and the extremely high resolution sampling of the state of California.

Trends in mean NDVI

Burned, unburned, and fire frequency

Mean NDVI values of burned pixels are significantly lower than unburned mean NDVI values within vegetation types, although this relationship is subtle. The relationship between NDVI and fire is well documented at small scales, and the present study compliments these results in that I found the relationships to hold true even at the statewide scale (Meng et al. 2015, Soulard et al. 2016). After looking at the results of the ANOVAs and linear regressions, it was apparent that fire was having substantial effects on all groups, but the directionality of the relationship varied by vegetation category. I also saw that in 6 of the 9 vegetation types, mean NDVI decreased as fire frequency increased, although this relationship was not linear as expected. Many categories showed initial peaks then sharp declines as fire frequency increased, a pattern that has been documented in the literature (Trabaud and Galtié 1996, Díaz-Delgado et al. 2002, Lesieur et al. 2002).

Grasslands- herbaceous. Grasslands are dominated by herbaceous monocots and small stature woody dicots (Dixon et al. 2014). The effect of fire on herbaceous plant assemblages are complex and can range from negative to neutral to positive (Gleason 1913, Hanson 1939). Because fires in grasslands often ignite and spread quickly, the basal portions of plants sustain little damage in these "cool" burns (Cheney and Sullivan 2008). Furthermore, the removal of litter by fire has also been shown to intensify growth in grasslands by increasing space, light, and nutrient availability. Seed germination is also often stimulated by burning, although yields have been shown to decrease when grasslands burn too frequently (Kozlowski 2012, Huenneke and Mooney 2012). These results are consistent with my findings in that at low fire frequencies, the mean NDVI of herbaceous habitats increased, but as fire frequency increased, mean NDVI showed a prominent decrease. Overall, grasslands may exhibit either increases or decreases in NDVI depending on the type of vegetation that burned and the frequency and intensity of the fire.

Mediterranean- oak and hardwood. Oak and hardwood species in the Mediterranean climate zone of California are highly resilient and adapted to fire (Naveh 1975). Mediterranean plants are known to exhibit a positive feedback with fire, where increased reproduction and accelerated post-fire vegetation regrowth allow plants to overcome the stress of being burned (Kozlowski 2012). Many oak species also experience re-sprouting from their root systems and can even survive the loss of all aboveground biomass from fire (Díaz-Delgado et al. 2002). Seemingly in contrast, my results showed a negative relationship between these two vegetation categories and burning. This relationship could be due to confounding unmeasured landscape factors or spatial differences in fire occurrence, and underscores the need for further species-specific investigations. There is also evidence in the literature that the productivity of oaks is similar to that of chaparral species after fire, which resembles my finding in that as fire frequency increases, oak and hardwood mean NDVI drops to that of chaparral, and then even lower to that of deserts (Kozlowski 2012). The sudden drop in mean NDVI seen between frequency 5 and 6 might be an artifact of low sample size, but it is interesting that both categories exhibit the same anomaly. Oaks and hardwoods may also be replaced with shrubs exhibiting pyrophytic behavior when burned too frequently, and this may be another explanation for the drop in mean NDVI seen in my results (Bowman et al. 1988, Kozlowski 2012).

Temperate forest- conifer and mixed Forest. In forests, burning can reset succession to pioneer stages by acting as a retrogressive agent, and after repeated burnings forest composition and structure may become dominated by fire resistant shrubs and trees (Kozlowski 2012). Although fire can have a deleterious effect on forests, it has also been shown to be a key factor in maintaining the productivity of valuable trees such as Douglas fir by increasing nutrient availability, clearing the understory, and increasing overhead light penetration (Spies and Franklin 1991). Consequently, through the creation of a more open canopy, fire may inherently reduce NDVI in forests, yet this may not be an indicator of poor forest health; high NDVI does not always perfectly correspond to vegetation health, it is simply a tool to estimate greenness. Additionally, although we see a negative mean NDVI slope between both burned and unburned pixels and with increasing fire frequency in the conifer and mixed forest categories, it is hard to discern whether this is due to vegetation replacement, timber harvest, or stand death. Considering my vegetation categories span a large variety of species with different dispersal strategies, fire resistance levels, and shade tolerances, it is hard to make general statements about the mechanism causing these patterns.

Chaparral- shrub. Chaparral communities exist in Mediterranean-type climates and are dominated by sclerophyllous shrubs with extensively branched root systems that adapt these plants to the hot rocky slopes they inhabit (Kummerow et al. 1977). Consistent with my expectations, I found that burned pixels had higher mean NDVI values than unburned pixels. This relationship was not surprising since chaparral is a fire induced-vegetation type and is able to persist well in fire prone areas (Keeley 1986). It was also interesting that as fire frequency increased, the shrub category maintained a level slope at intermediate fire frequencies, although it eventually started declining more quickly at high fire frequencies. This pattern could be because many shrub species are negatively affected by short fire return intervals, which causes large kills of vulnerable sprouting plants and decimation of seedlings (Zedler et al. 1983, Haidinger and Keeley 1993). Paradoxically, some species have also developed characteristics that make them highly flammable and reliant on recurring fires for optimal health (Bond and Midgley 1995, Cowan and Ackerly 2010). Likewise, several chaparral species' seeds lie dormant in the soil for long periods of time until burning activates them (Keeley 1986, 1987). Furthermore, when fire burns through chaparral it consumes most biomass and initiates new succession, where gaps are easily filled in with new or dormant species that may have greater NDVI values than that of species present in the climax community (Kozlowski 2012). Since so many different species comprise my shrub category, it is difficult to determine the exact reasons for the pattern we see, but overall fire is having a positive or neutral effect on shrubs in my analysis.

Other, agriculture, and desert. The other and agriculture categories showed interesting patterns in their results, but because they are human managed landscapes, it is difficult to infer the relationship between fire and mean NDVI without more information. On the other hand, deserts are well-studied, and exhibited increased NDVI with both burn occurrence and increasing fire frequency. Although prevalence of fires is relatively low in deserts, the effect fire has on the landscape can be severe (Brown and Minnich 1986). Grass species usually sustain little fire damage because of the rapid way fires move through them (Cheney and Sullivan 2008). Conversely, woody species require several years to regrow and repeated burning keeps the plant in a juvenile stage (Kozlowski 2012). This differing susceptibility of woody species and grasses to fire makes attributing the positive relationship between mean NDVI and fire frequency to fire itself difficult. However, to support the argument that fire is responsible for the positive relationship, research has shown that fire may be controlling invasive species and allowing native plants to flourish, therefore increasing mean NDVI (Brooks and Pyke 2002, DiTomaso et al. 2006). External factors, such as human disturbance and climate change, may also be allowing for the establishment of invasive fire-resistant species that fill in patchy areas and create contiguous biomass, which could also increase NDVI (Brooks et al. 2004, Brooks and Matchett 2006, Brooks and Chambers 2011). Overall, the patterns revealed by these analyses are interesting, but require more spatially explicit and species-specific investigations.

Google Earth Engine

This study illustrates both the power of GEE to handle and analyze large raster datasets, as well as its processing and statistical limitations. The scale of this project made it nearly impossible to do without GEE's vast public data archive and parallel processing of each pixel. This is because traditional geospatial software requires users to store and upload their own datasets and the processing capability is restricted to the power of the desktop computer used (Yang et al. 2011). GEE on the other hand, utilizes cloud computing to efficiently analyze geospatial data (Hansen et al. 2013). While GEE is one of the most powerful raster calculators freely available, it's limitations are apparent. I found that although Google encourages their product to be used on a worldwide scale, their user memory limit makes it hard to even work on a state-wide scale. Furthermore, there is limited built in statistical functionality, and the site becomes difficult to use during peak times, forcing me to run computations on weekends and late at night. Despite these shortcomings, GEE was an invaluable tool, without which this kind of work would not be possible.

Statistical robustness of geospatial data

This study was caught between the conventions of ecology and the newer field of remote sensing, and consequently had to balance the statistical requirements of both fields. Problems in ecology are usually explained and presented with robust statistical tests, while geospatial science can often answer questions without the use of traditional statistics (Unwin 1996). Furthermore, methods of ecology hold assumptions that are almost never true with geospatial data such as equal sample size, homogeneity of variance, independence, and reproducibility (Elston and Buckland 1993). My study sought to answer an inherently spatial ecological problem within the bounds of traditional statistics, and consequently had to adhere to these assumptions. I found that due to my massive sample sizes, the line between statistical significance and biological significance became blurred. During my analysis, I also had to compromise the resolution of the data in order to reduce dimensionality so that statistical programs could analyze the vast amounts of data. Although I faced limitations, I still found the tests I used to be adequately powerful and robust to the difficult data I was working with.

Future directions

Although this study found statistical significance in the relationship between fire and NDVI, I will incorporate other external variables such as climate, aspect, and elevation, as well as measures of spatial autocorrelation and pseudoreplication into my future work. Most importantly, I hope to analyze each vegetation type at the species level, rather than in broad categories, to further clarify the species-specific responses to fire. The flexibility of GEE will allow me to do this as well as incorporate a temporal aspect into my analysis to measure regeneration before and after fire events. Understanding this complex relationship between fire, NDVI, and vegetation type is necessary in management, policy, and economic decisions throughout California.

Broader implications

In addition to providing significant ecological insight into the effects of fire on California's landscape, this research is also an important tool for land managers who want to allocate scarce fire resources to vegetation categories that show poor regrowth. Using these results, decision makers will also be able to identify and monitor vulnerable locations, such as those in the Southern Sierra Nevada mountains and the South Coast, that have high fire frequency and low NDVI. Furthermore, as the climate continues to change, there is evidence that the frequency and severity of fires is increasing in California, and broad-scale quantitative studies like this are becoming increasingly important (Westerling et al. 2006, Miller et al. 2008).

My use of Google Earth Engine also provides a useful case study of the benefits and limitations of this new geospatial tool. Although the limitations decreased how efficiently I could work, the tool itself made this type of broad spatial and temporal scale research possible. As GEE improves, and more geospatial cloud computing interfaces become available, new and important insights into contemporary and historic patterns of fire and vegetation will be possible.

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APPENDIX A: Full Map of Burned and Unburned Areas

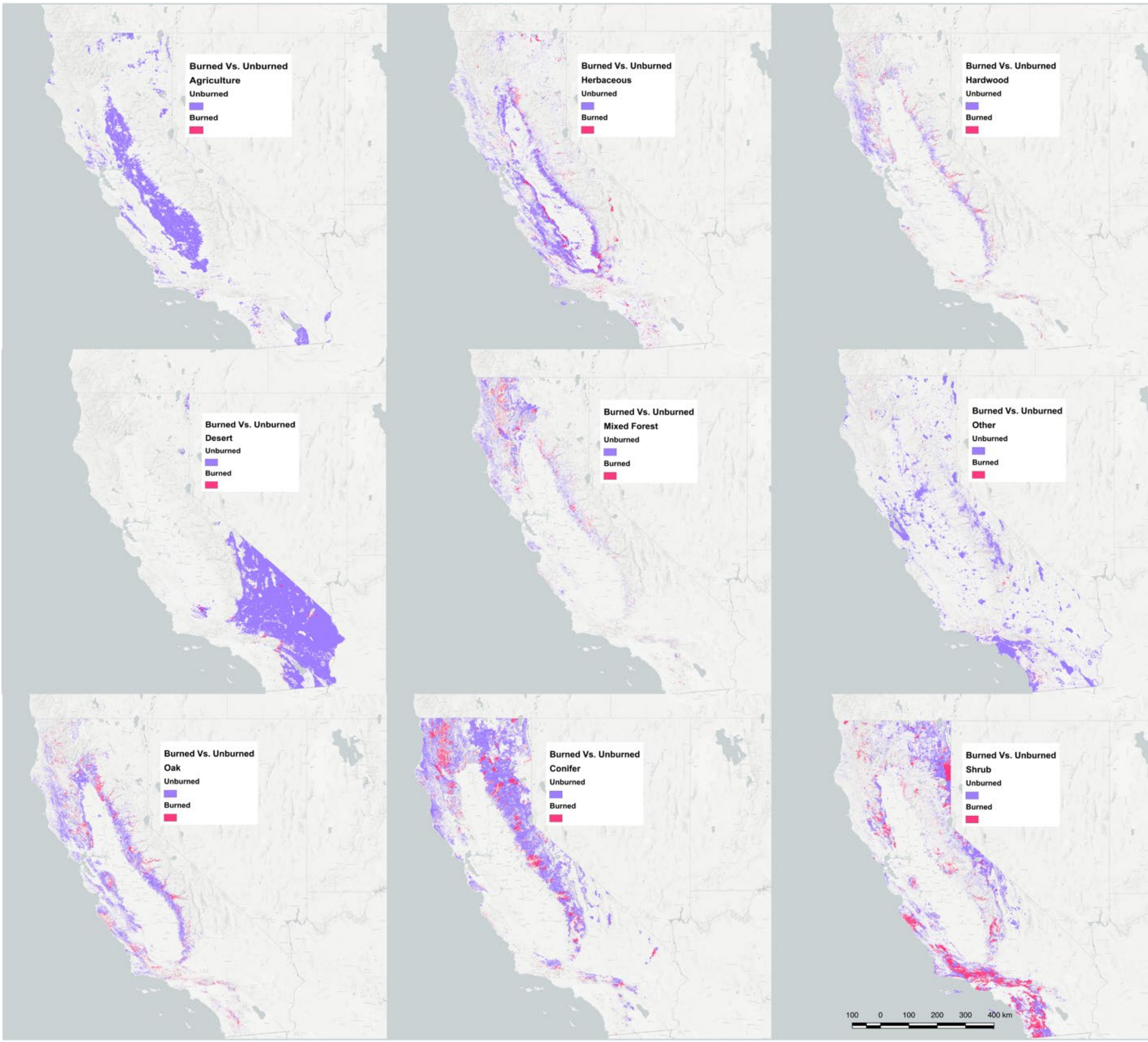

Figure A1. Maps of burned and unburned areas by each vegetation category. Burned areas are shown in pink and unburned burned areas in purple. It is apparent that some categories burned more than others, for example, shrub has much more red than the desert and agriculture categories.

APPENDIX B: Full Map of Fire Frequency

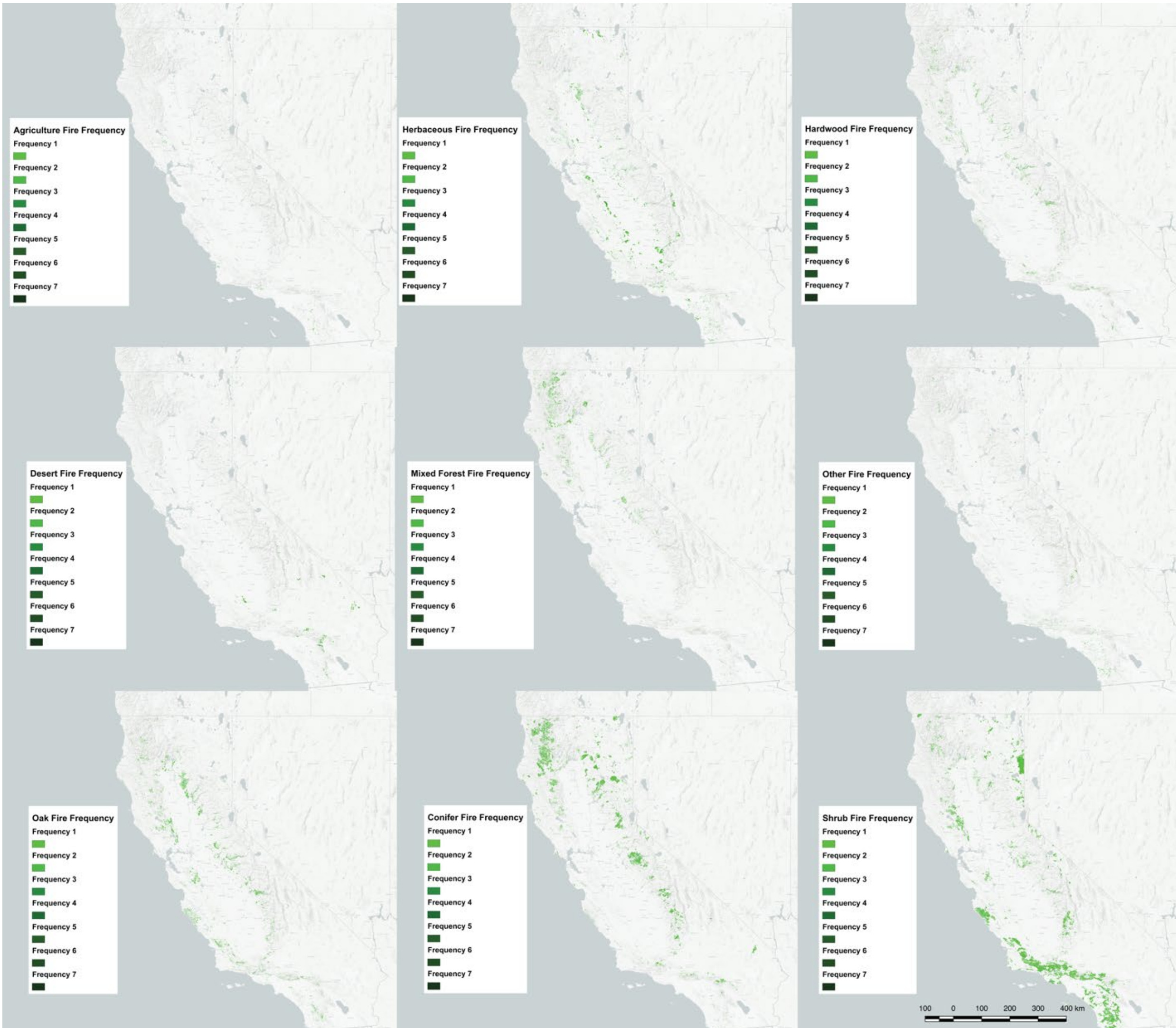

Figure A2. Map of fire frequency for each vegetation category. Increasing fire frequency is represented by increasingly dark colors of green. Some areas exhibit more frequent fires, for example, the shrub and conifer categories, while other exhibit very little burning at all, for example, the agriculture category.