Impacts of High Severity Wildfire on Vegetation Type Conversion in Southern California Chaparral

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ABSTRACT

California has been experiencing more historically large, high severity wildfires, prompting managers to investigate the potential long-term impacts of this disturbance on biodiversity. There has been an emphasis on management within forested ecosystems, with less attention turned to historically infrequent, high severity fire regime ecosystems such as Southern California chaparral. To study the effects of a contemporary large-scale, high severity wildfire on chaparral, I investigated the effects of the 2017 Thomas Fire on vegetation type conversion within Santa Barbara and Ventura counties, extending into the adjacent Los Padres National Forest. This was accomplished through a combination of Random Forest supervised classification, burn severity analysis using dNBR, and a comparative analysis between burn severity classes and type conversion. I found that the classification schema I developed was 68% accurate. Overall, there was a similar proportion of vegetation change across the study area, but the areas burned that were classified as forested (Conifer, Hardwood) pre-fire had a greater occurrence of being type converted to Shrubland. The Shrubland class within the study region experienced a succession of varying vegetation types. The Thomas Fire was categorized as mostly low to moderate severity, and there was some correlation between higher burn severity classes and certain types of vegetation change. This validates other research that assesses the dynamics of post-fire vegetation succession and reaffirms the need for future study on the effects of changing spatial and severity patterns on chaparral.

KEYWORDS

Remote sensing, supervised classification, Thomas Fire, vegetation mapping, dNDVI

INTRODUCTION

In recent decades, California has seen an increase in the size, frequency, and severity of wildfires, raising questions about best practices for ecological management in the future that addresses both human safety and ecosystem health (Buechi et al. 2021, Williams et al. 2019, Dennison et al. 2014). One of the most impactful drivers of this fire regime change has stemmed from over a century of policies implemented to prevent wildfires from occurring at all costs and suppress fire as soon as it begins (Grabinski et al. 2017). As a result of this, many ecosystems have shifted to having larger accumulations of fuels, changes in stand structure for many forests, and an increase in forest ladder fuels that causes more crown fires and greater plant mortality (Cortenbach et al. 2019). These larger, more severe wildfires have caused widespread changes in many of California's ecosystems, some of which may be permanent due to stand replacing fires or compounding effects of disturbance such as drought followed by wildfire (Davis et al. 2019). In addition, a changing fire regime characterized by more frequent fires can potentially endanger some of California's most unique ecosystems, including the chaparral shrubland.

Chaparral ecosystems are characterized by a closed canopy, sclerophyllous shrub cover as the dominant vegetation type, and a fire regime that is infrequent yet produces severe wildfires (Davis and Michaelsen 1995). However, the severe fires that are characteristic of this ecosystem do not cause plant mortality; instead, they act as the catalyst for base resprouting shrubs and seed banks that require heat for germination (Tyler 1995). Most of the plant species in chaparral reestablish within 10 years following a fire, but if the return interval between fires is too short, these species cannot reestablish before the next fire (Zedler et al. 1983). This could lead to vegetation mortality and the potential for type conversion (Hope and Clark 2007). Factors such as habitat fragmentation, drought and a changing fire regime have compromised chaparral, allowing vegetative type conversion (VTC) to take place (Syphard et al. 2022).

VTC is a process by which the dominant category of vegetation within a given ecosystem changes, potentially affecting other ecological components of the area in question (Syphard et al. 2019). Historically, the closed canopy structure has made chaparral resilient to type conversion, because it blocks light so invasive grasses cannot establish (Park and Jenerette 2019). Type conversion can be caused by drought in chaparral, and the resulting shrub mortality causes openings that allow invasive grasses to establish (Jacobsen and Pratt 2018, Okin et al. 2018, Keeley et al. 2022). Once chaparral has type converted to grassland, it is difficult to restore the previously closed canopy structure. There is a growing body of research assessing the dynamics between fire exclusion, drought, and wildfire in forested ecosystems, but less is known about the effects of these dynamics on chaparral and the implications for future management strategies.

Additionally, it is worth noting the impact of land management by Indigenous communities in shaping the community dynamics of chaparral. Much of our current understanding of ecological plant communities lies in the definition of the "historical" fire regime, or the idealized landscape in which ecosystem management often strives to return to (Conard and Weise 1998). However, empirical evidence has shown that prior to colonization by European settlers in the late 18th century, chaparral, as many other ecosystems within California, was managed with cultural burning by Indigenous people (Anderson and Rosenthal 2015, Anderson and Keeley 2018). Among other management objectives, burning was used by these communities to generate landscape mosaics, cultivate fire adapted plant species of interest, and provide easier access to resources such as game animals that were otherwise blocked by the dense canopy of chaparral shrubs (Kimmerer and Lake 2001). For these reasons, discussions of land management in chaparral should consider the historical context of human interactions with the landscape when determining our own modern objectives, while still consulting with the communities that discovered the multiple facets of chaparral through the use of Traditional Ecological Knowledge.

In this study, I assessed the ways in which severe wildfire impacts vegetation recovery and possible conversion in chaparral ecosystems. To accomplish this, I investigated three sub-questions, studying the 2017 Thomas Fire: (1) How did vegetation types change from 2015 to 2022? (2) What is the distribution of burn severity in the Thomas Fire burn scar? (3) Is there a correlation between burn severity and type conversion? I hypothesized that vegetation type will change following the large disturbance, favoring a greater succession of herbaceous vegetation compared to shrubs in the burned areas, and conversion from forest to shrubland in more wooded areas. The Thomas Fire has been characterized as a predominantly intense, high severity fire, so I predicted that I would find similar spectral signatures in my NBR calculations. Finally, I predicted that the extent and varieties of type conversion found would vary with burn severity. To investigate these questions, I developed a supervised classification schema using data from CALFIRE's FVEG land cover data in 2015, assessed the extent of burn severity using data sourced from MTBS, and calculated dNBR across the entire study area. Finally, I performed a spatial comparative analysis between the extent of vegetation change within the burned and unburned areas and compared the types of change I found within the different burn severity classes.

METHODS

Study system

The study system of interest is located in Santa Barbara and Ventura counties, CA. It is characterized by a Mediterranean climate, with warm, dry summers, cool winters, and most precipitation occurring between the months of October and April (Oakley et. al 2019). However, the precedence of years-long drought between 2012 and 2016 may have impacted this typical seasonality (Okin et al. 2018). Most of the vegetation in the study area is chaparral shrubland, although some areas are classified as coastal sage scrub, mixed conifer, and hardwood as well (CALFIRE 2015). For this study, the particular area of interest is located within the burn boundaries of the 2017 Thomas Fire, as well as a portion of area located to the north of the burn scar area within Los Padres National Forest. Despite being a somewhat different land cover distribution (more hardwood and mixed conifer forests than below, yet still including some shrubland), it is still a useful control as the topography of the region is similar to that of the burn scar area to the South (Figure 1).

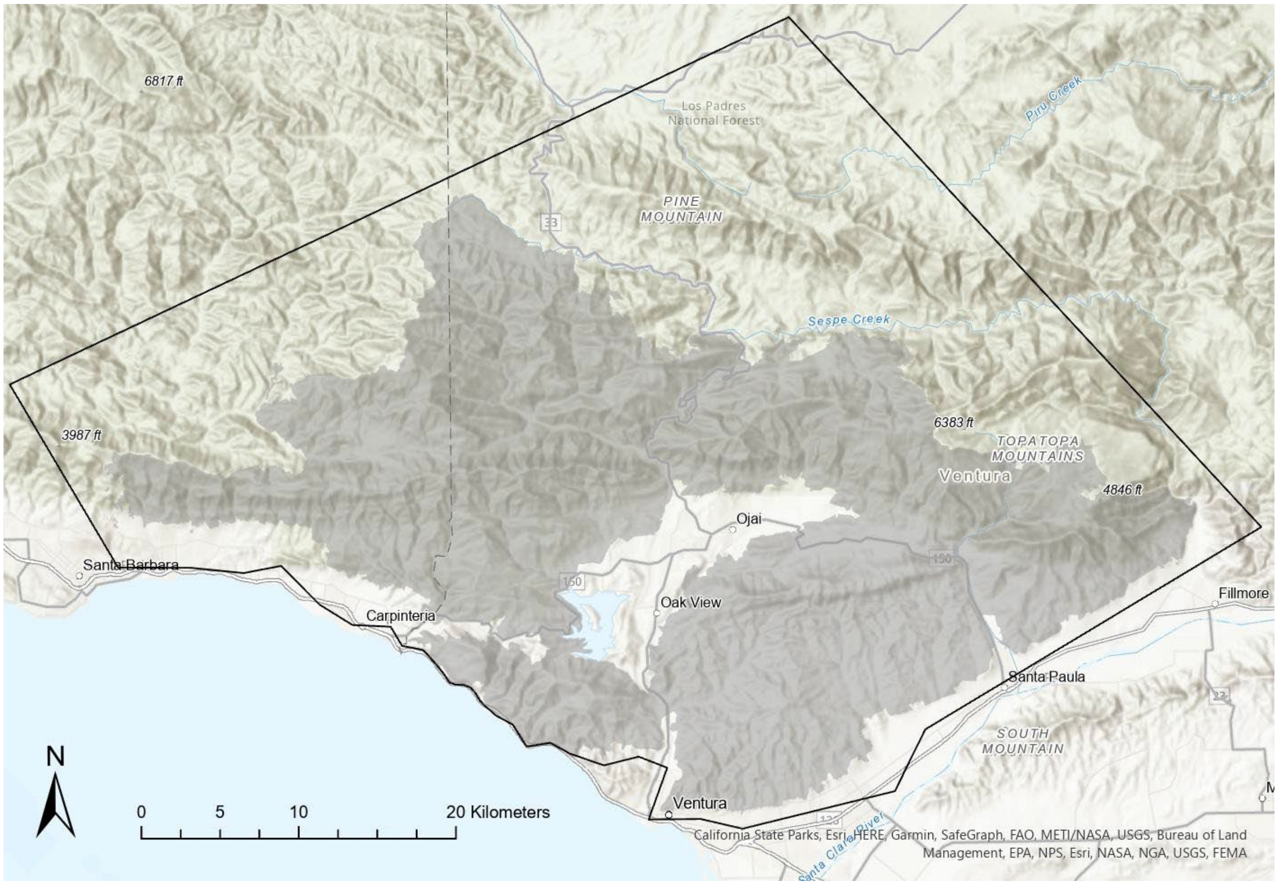


Figure 1. Map of the study area. This map displays the outline of the AOI and the burn area of the Thomas Fire.

The Thomas Fire ignited on December 4th, 2017, and rapidly spread due to historic Santa Ana katabatic wind events through the first few weeks of the fire (Kolden and Henson 2019). It burned nearly 282,000 acres and was declared fully contained on January 12th, 2018, after heavy rainfall helped aid suppression efforts (Kuyper 2018). The fire significantly burned areas of the Los Padres Forest, the surrounding watershed, and the Santa Ynez mountains. At the time of full containment, it was briefly the largest wildfire in California recorded history (Fovell and Gallagher 2018).

Vegetation change

dNDVI

NDVI is calculated by taking the normalized difference of the Red and NIR bands in a multispectral image, with values closer to 1 indicating higher reflectance and greener vegetation

(USGS 2022). However, chaparral has on average lower NDVI values due to the prevalence of shrubs and grass and notable absence of forested canopy; as such, it can be challenging at times to determine land cover classes from NDVI values alone (Hernández-Clemente et al. 2009). In this study site, I calculated the change in NDVI (dNDVI or ΔNDVI) between the months of May and September, as herbaceous vegetation tends to have similar spectral reflectance to shrubs in the spring, but has a sharp decrease come fall when the vegetation desiccates (Paruelo and Lauenroth 1998, Rundel 2018). This assisted in creating a more distinct image to delineate shrubs from grasses, as well as provide an additional input to the supervised classification schema I created.

$$NDVI = (NIR - Red) / (NIR + Red)$$
$$\Delta NDVI = NDVI_{pre} - NDVI_{post}$$

Supervised classification

To classify vegetation type from remotely sensed data, I used existing vegetation maps sourced from CALFIRE in 2015 as part of a Random Forest supervised classification system to separate different vegetation types before the effects of the Thomas Fire (Saini 2023). I downloaded the FVEG land cover data from CALFIRE's Fire and Resource Assessment Program (FRAP) as well as two Landsat 8 images sourced from USGS EarthExplorer (one taken on May 3rd, and the other on September 24th, 2015). I first preprocessed the images by removing cloud cover and trimming them to my area of interest. Then, I adjusted the band combination of the images to a composite of bands 4, 5, and 7. This included the Red, NIR, and SWIR2 bands of Landsat 8 imagery and provided a greater contrast in the spectral reflectance of different vegetation types. For example, compared to a true color image, the spectral reflectance of forested areas was contrasted more strongly with lower reflectance vegetation such as grass.

The vegetation classes that I used were modeled after the "Life Form" classes from the FVEG land cover map, and included 8 different classes: Shrubland, Herbaceous, Conifer, Hardwood, Agriculture, Barren/ Other, Urban, and Water (Figure 2). The first six classes were used in the subsequent vegetation type analysis, while the "Urban" and "Water" classes were included for accurate classification, yet I did not include them in my later change detection process. I followed a standard Random Forest supervised classification workflow from the Classification

Wizard, which is part of the "Image Analyst" package in ArcGIS Pro (Esri 2023). The first step included segmenting the images of interest to group pixels into clusters with similar spectral characteristics to one another. Then, I created training polygons by cross-referencing the FVEG land cover data with my composite reflectance images and formed a total of 460 training polygons as inputs to the classifier— 60 for each class excluding Shrubland (80) and Water (20). Next, I ran the classifier on the original composite band image, using the training polygons from my segmented images and the dNDVI calculated between May and September of 2015 as inputs to the classification schema. The output was a classified image by life form of the original composite. This was repeated for May and September 2015.

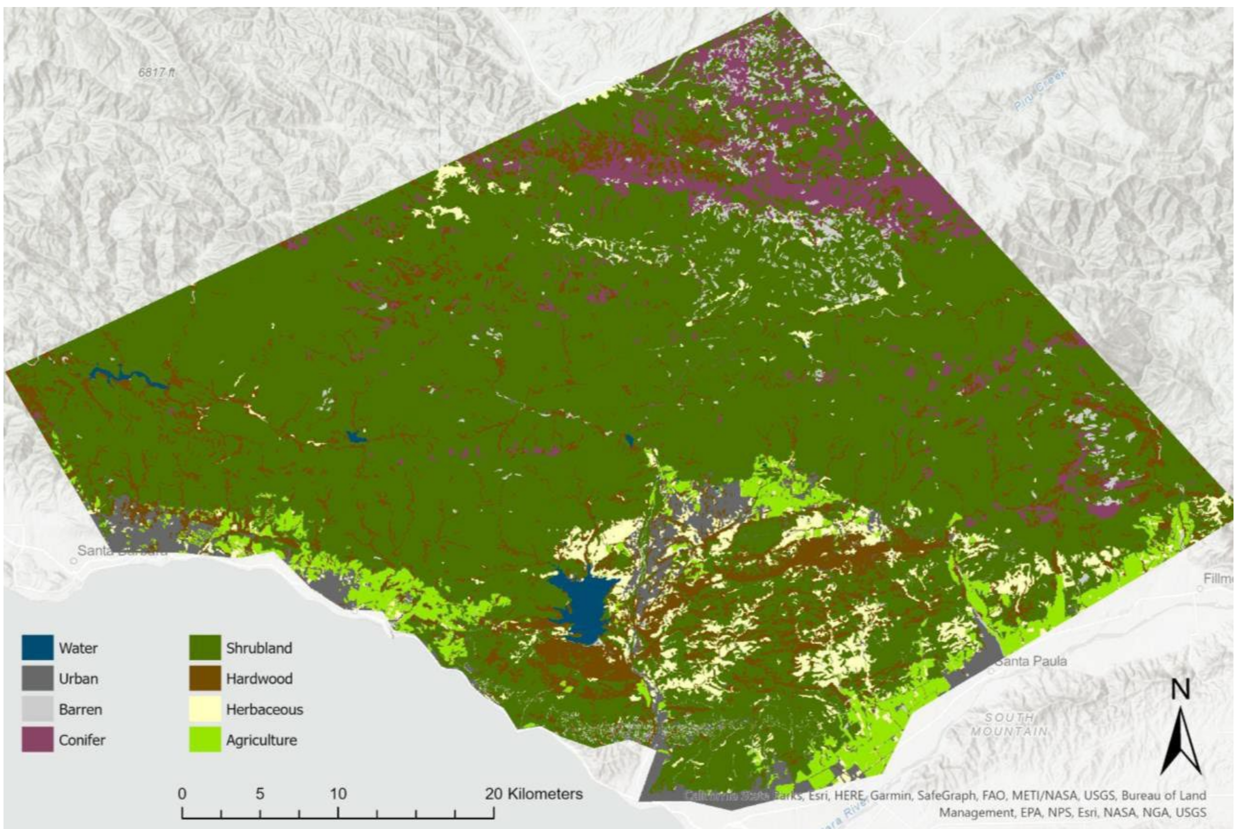


Figure 2. FVEG 2015 land cover map. This map represents the ground truth used to determine the accuracy of my classification schema.

Analyzing vegetation change

To determine the accuracy of my supervised classification method, I performed a confusion matrix on both classified images for 2015, using the original FVEG land cover map as my "ground truth" data. I generated 126 random points across the entirety of the AOI from the "Create Accuracy Assessment Points" tool. I had originally specified 100 random points, which were adjusted by ArcGIS Pro's stratified random sampling to have an equal number of training points proportional to the area of each class. I then compared the values of the classified raster at each training point to the FVEG land cover map and used those points to generate a confusion matrix using the "Compute Confusion Matrix" tool. This compared the data generated using dNDVI and the vegetation composite as inputs to see if they could accurately distinguish the different vegetation classes at a 30-meter pixel resolution. This was also performed in ArcGIS Pro and required the Image Analyst license and toolbox (Esri 2023).

Applying the classifier to 2022 data

Once the confusion matrix was generated, I used the most accurate classification schema on the respective month in 2022, which was from September 2015. The same steps were repeated as with the 2015 classification workflow, but I replaced the dNDVI and segmented images with the corresponding raster data from 2022. The two rasters I used for analysis were from Landsat 9 multispectral images, captured May 16th and September 3rd, 2022, and processed in the same way as before. I did not edit my training polygons if it seemed that the spectral characteristics were similar to the previous training polygons, although I did change the schema slightly, including adding an additional 20 training polygons to the "Barren/ Other" class for more accurate training (480 total). There was a notable lack of both classified land cover maps and satellite imagery available at a spatial resolution fine enough to distinguish different vegetation types, and as such, I omitted the confusion matrix analysis from the post-fire classification.

Burn severity analysis

dNBR

To determine the average burn severity in each vegetation class, I calculated dNBR across the entirety of the burned area, using the same Landsat 8 multispectral data from USGS for pre-fire (2017) and post-fire (2018) years using the available tools for band index calculations in ArcGIS Pro. NBR is used as a metric to quantify vegetation stress and is the normalized difference between the NIR and SWIR bands of a multispectral image. In comparison, dNBR (ΔNBR) shows the overall burn severity by subtracting the post-fire NBR from the pre-fire NBR in each pixel, on a scale from -1 to 1, with higher values indicating more severely burned areas. NBR is typically scaled by a factor of 10^3 to give an integer value in each pixel, and USGS has provided a standard scale to assess severity based on the dNBR of a site (Table 1).

$$NBR = (NIR - SWIR) / (NIR + SWIR)$$

$$\Delta NBR = NBR_{pre\text{-}fire} - NBR_{post\text{-}fire}$$

Table 1. Burn severity classes from calculated dNBR values. Proposed by the U.S. Geological Survey.

Severity Level	dNBR Range (scaled by 10^3)	dNBR Range (not scaled)
Enhanced Regrowth, high (post-fire)	-500 to -251	-0.500 to -0.251
Enhanced Regrowth, low (post-fire)	-250 to -101	-0.250 to -0.101
Unburned	-100 to +99	-0.100 to +0.99
Low Severity	+100 to +269	+0.100 to +0.269
Moderate-low Severity	+270 to +439	+0.270 to +0.439
Miderate-high Severity	+440 to +659	+0.440 to +0.659
High Severity	+660 to +1300	+0.660 to +1.300

However, severity is relative due to the nature of chaparral, with a primary characteristic of a typical chaparral fire regime being high severity crown fires (Tyler 1999). Additionally, dNBR can sometimes indicate vegetation stress and mortality from drought (Sun et al. 2006). For this reason, I selected available imagery with minimal cloud cover that was closest to the start and end dates of the Thomas Fire (October 22nd, 2017, and February 11th, 2018), aiming to minimize the spectral influence of effects on vegetation from the 2012 to 2016 drought. This fire took place at the end of the multiyear drought, and as such caused highly flammable desiccated vegetation to burn, which typically has a lower spectral signature than wildfires in other vegetation types (Keeley et al. 2022).

Burn severity comparison

To validate my remotely sensed burn severity data, I compared my calculated dNBR map to the geospatial data on burn severity for the Thomas Fire from Monitoring Trends in Burn Severity. This raster dataset was downloaded from MTBS for fires that occurred in California in 2017, then trimmed to only include the perimeter of the Thomas fire. MTBS data accounts for both burn severity indices such as dNBR, as well as other factors including vegetation mortality to calculate their severity classes. For the Thomas Fire, the raster dataset was organized into five severity classes, from no change (1) to high severity (5). After converting the MTBS severity classes to polygons to create 5 different "Zones", I exported the zonal statistics of the dNBR map to a table in ArcGIS Pro. This allowed me to calculate statistics for the dNBR values, including the mean, standard deviation, and range for each burn severity class.

Extent of vegetation change

To determine if there was a significant difference in type conversion between the burned and unburned areas within my AOI, I used the "Change Detection" workflow in ArcGIS Pro to first generate an output map that displayed each pixel that had converted from one vegetation type to another between 2015 and 2022. This led to 30 classes, with the six vegetation classes as both possible "From" and "To" classes. I then separated these classes into two areas: Inside and Outside of the burn perimeter and converted each dataset into isolated polygons grouped by type conversion class. This allowed me to compare the proportions of the vegetation change, grouped by 2015 and 2022 vegetation type. I then exported the area data to Microsoft Excel to graph the vegetation change grouped by pre-fire vegetation type.

These steps were repeated for the unburned areas, using the September 2022 classified raster and the "Extract by Mask" tool to remove the pixels that had been type converted between 2015 and 2022. This allowed me to have a comparative baseline, and appropriately scale the extent of the vegetation change in comparison to the areas that remained the same. I then converted this raster into a polygon shapefile and exported the area data from the attribute table to Excel to add a control ("No Change") class to my graphs.

Comparing burn severity to type conversion

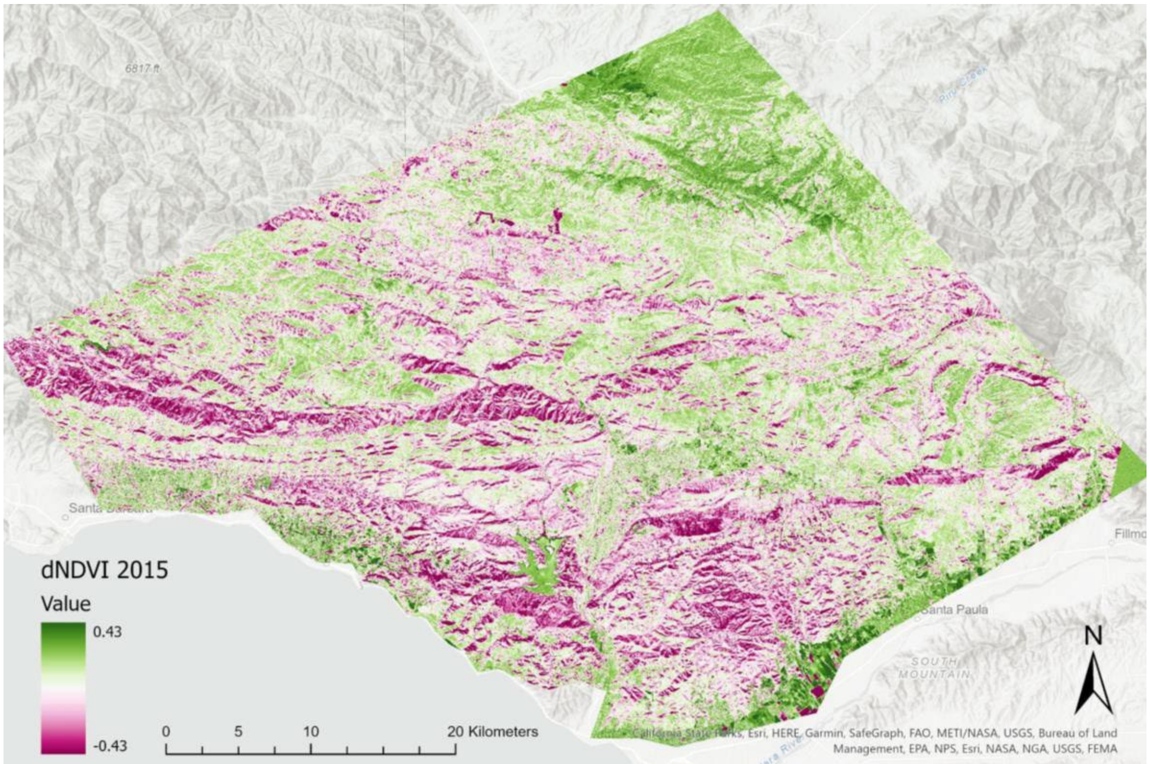
To determine the impacts of burn severity on type conversion, I clipped the MTBS data to the different polygons created from the change detection raster using the "Extract by Mask" tool. This allowed me to isolate the different areas that had been both type converted and burned, and see if there were any trends in the classes of change within the burn perimeter. I then exported the attribute table that included both burn severity class and type conversion class by area to Excel to graph the relative changes in vegetation type by burn severity.

RESULTS

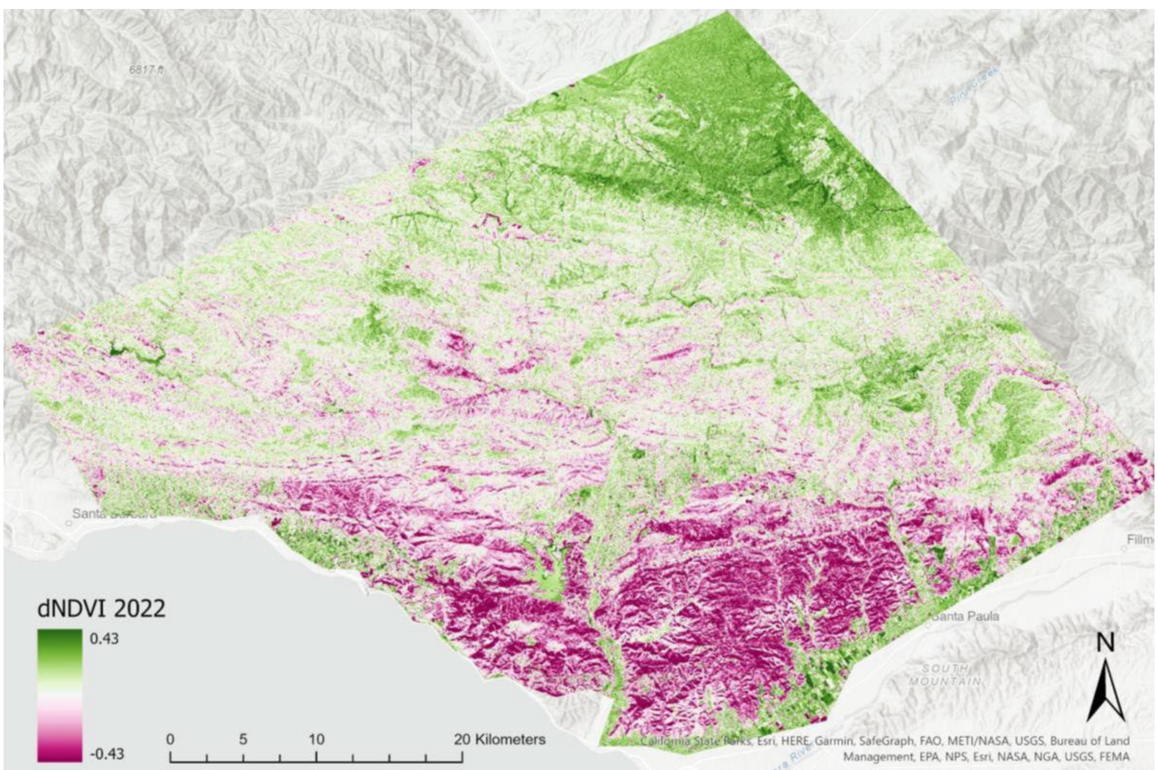
Vegetation change

Comparison of Seasonal NDVI

I found that between the two study years, the change in NDVI within a given year (May - September) was within approximately the same range, with the majority of values falling between -0.4 and 0.4 (Figure 3a-b). In 2022, the distribution of NDVI has changed somewhat, with a higher proportion of NDVI decline in the southern regions, indicating a potential sign of type conversion. Additionally, I observed that regions that experienced little to no variation in NDVI in the North in 2015 showed a more positive distribution in 2022. The average dNDVI value had decreased overall in 2022 (-0.06) compared to 2015 (0.02), which can also indicate a shift in vegetation type due to differences in seasonal NDVI fluctuations between cover classes (Figure 4).



(a)



(b)

Figure 3a and 3b. Maps of dNDVI for 2015 and 2022. This shows the seasonal variability of NDVI in the study area between May and September of 2022. The burn scar of the Thomas Fire is faintly visible in the 2022 map.

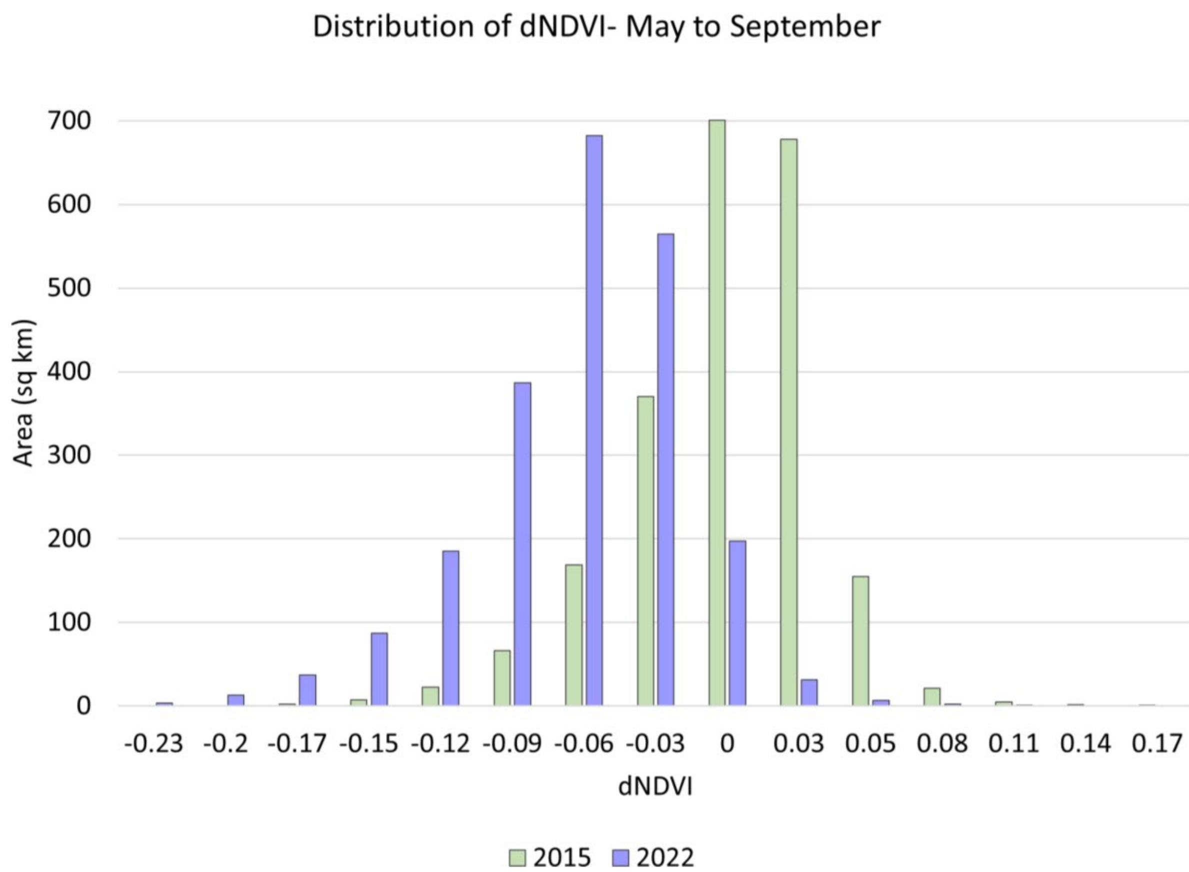
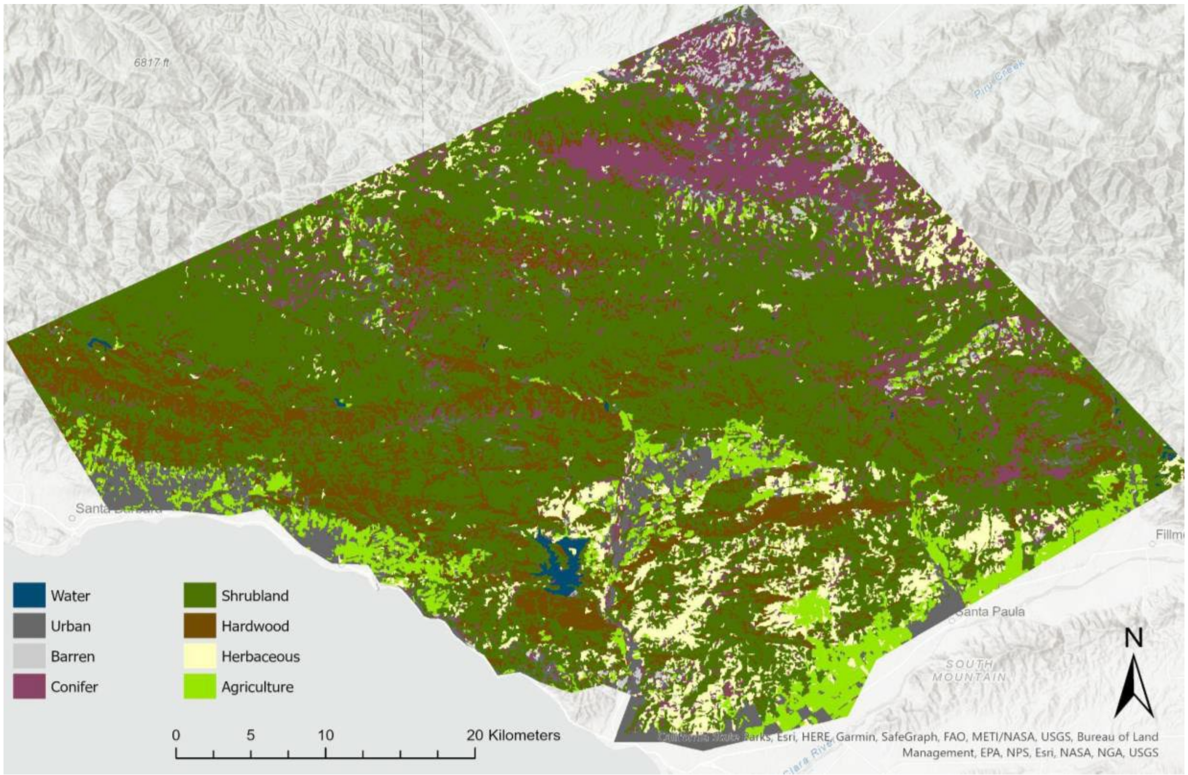


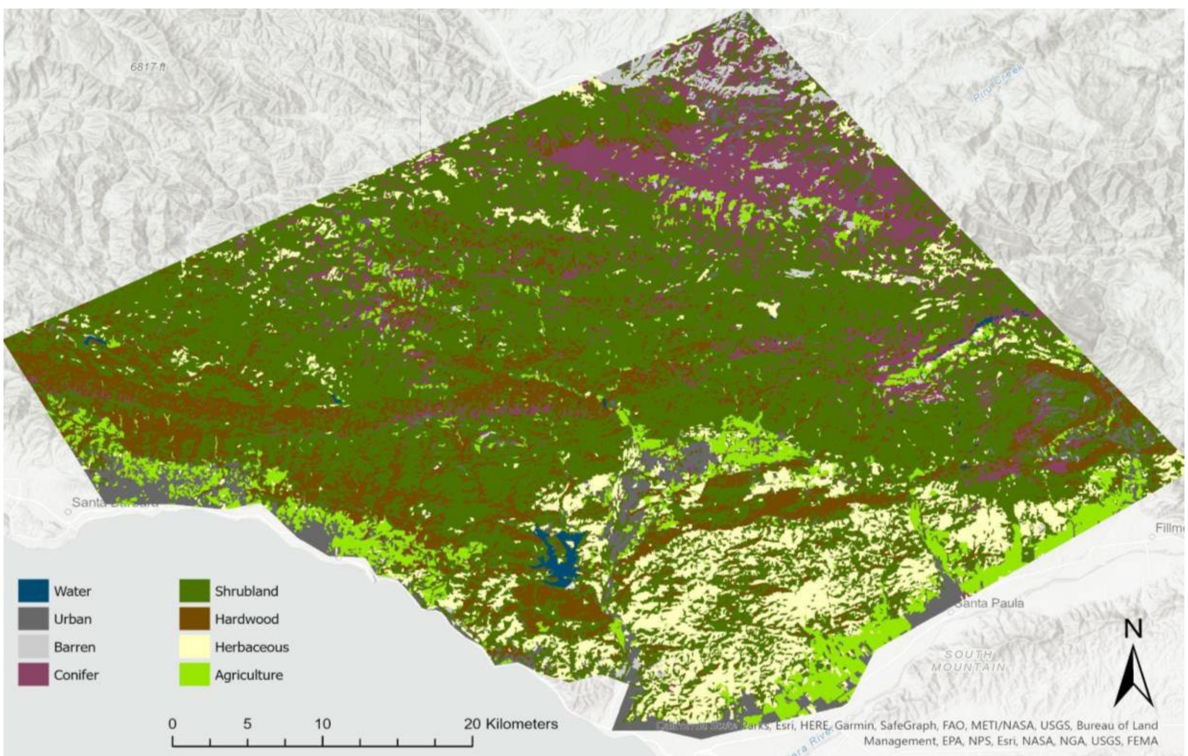
Figure 4. Change in seasonal NDVI. The distribution of seasonal variation of NDVI from 2015 to 2022.

2015 Classification

There was slight variation in the land cover distribution found in the seasonal maps. In May, there was a higher proportion of all vegetation cover types except for the Herbaceous class (Figure 5a-b). More areas were classified as Herbaceous in September of 2015, but I also determined that the accuracy assessment was higher in September than May (Figure 6).



(a)



(b)

Figure 5a and 5b. Land cover classification maps for (a) May and (b) September 2015.

Classification Accuracy

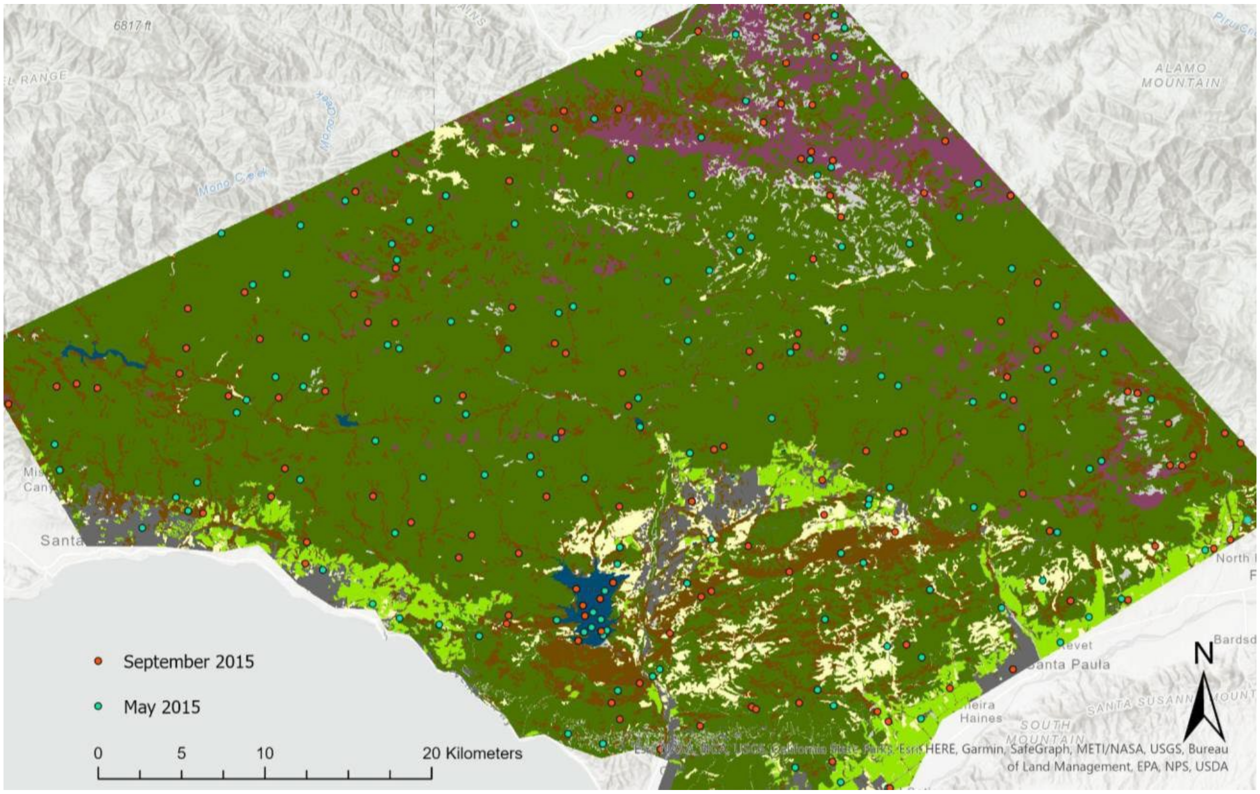


Figure 6. Randomly generated points for accuracy assessment. These were the points generated from a stratified random sampling method and used as the input for the confusion matrix. The background map is the ground truth data from FVEG 2015 (California Department of Forestry and Fire Protection).

May. I found that the overall accuracy of the Random Forest classification schema was 61% in May. The classes with the highest user accuracy included Agriculture (70%), Water (80%), and Shrubland (83%). In comparison, the classes with the highest producer accuracy included Urban (71%), Water (80%) and Agriculture (88%).

From the confusion matrix that I calculated, errors of omission were highest in the Shrubland (42%), Hardwood (50%), and Barren (60%) classes. Additionally, errors of commission were highest in the Hardwood/ Conifer (64%), Herbaceous (70%), and Barren (80%) classes. The Kappa coefficient was 0.46, indicating a 46% overall agreement between classified and ground truth data (Table 2).

Table 2. Confusion matrix for vegetation classification accuracy of May 2015.

Class	ID	10	20	30	40	50	60	70	80	Total	U Accuracy	Kappa
Water	**10**	8	1	0	0	1	0	0	0	10	0.8	
Urban	**20**	0	5	1	1	1	2	0	0	10	0.5	
Barren	**30**	0	0	2	0	8	0	0	0	10	0.2	
Conifer	**40**	0	0	0	4	6	1	0	0	11	0.36	
Shrubland	**50**	1	1	2	1	45	2	2	0	54	0.83	
Hardwood	**60**	0	0	0	0	9	5	0	0	14	0.36	
Herbaceous	**70**	1	0	0	0	5	0	3	1	10	0.3	
Agriculture	**80**	0	0	0	0	3	0	0	7	10	0.7	
Total		10	7	7	6	78	10	5	8	129		
P Accuracy		0.8	0.71	0.4	0.67	0.58	0.5	0.6	0.88		0.61	
Kappa												0.46

September. I found that for September 2015, the overall classification accuracy was 68%. The highest user accuracy was found for Agriculture (80%), Shrubland (87%), and Conifer (90%), while the highest producer accuracy was in Water, Urban, and Herbaceous, all with a producer accuracy of 100%.

Errors of omission were highest in Conifer (40%), Hardwood (47%), and Barren (60%) classes. Errors of commission were highest in Hardwood/ Herbaceous (50%), Urban (70%) and Barren (80%) classes. The high error rate with the Barren class can potentially be attributed to FVEG classifying the land cover type as Barren/ Other, while the primary input polygons I trained emphasized only the barren land cover surface reflectance values. In September 2015, the Kappa coefficient for the confusion matrix was 0.57, indicating a 57% agreement between the classified raster and ground truth data (Table 3).

Table 3. Confusion matrix for vegetation classification accuracy of September 2015.

Class	ID	10	20	30	40	50	60	70	80	Total	U Accuracy	Kappa
Water	**10**	7	0	0	0	2	1	0	0	10	0.7	
Urban	**20**	0	3	1	0	4	1	0	1	10	0.3	
Barren	**30**	0	0	2	4	3	1	0	0	10	0.2	
Conifer	**40**	0	0	0	9	1	0	0	0	10	0.9	
Shrubland	**50**	0	0	2	2	45	3	0	0	52	0.87	
Hardwood	**60**	0	0	0	0	7	7	0	0	14	0.5	
Herbaceous	**70**	0	0	0	0	5	0	5	0	10	0.5	
Agriculture	**80**	0	0	0	0	2	0	0	8	10	0.8	
Total		7	3	5	15	69	13	5	9	126		
P Accuracy		1	1	0.4	0.6	0.65	0.53	1	0.89		0.68	
Kappa												0.57

2022 Classification

The results of the 2022 classification had a similar distribution of classes to the September 2015 classification output (Figure 7). Of the 2,202 square kilometers of the study area, 989 sq km, or 45% of the total study area was classified differently in 2022 compared to its 2015 vegetation class. The greatest negative change in total land cover was in the Herbaceous class, with a relative 81% decrease in area. The classes with the greatest relative increases were Shrubland (8%), Conifer (60%), and Barren (282%). The class with the greatest change overall was also Herbaceous cover, which decreased by 185 km between 2015 and 2022, while the greatest overall increase was in the Agriculture class (Table 4).

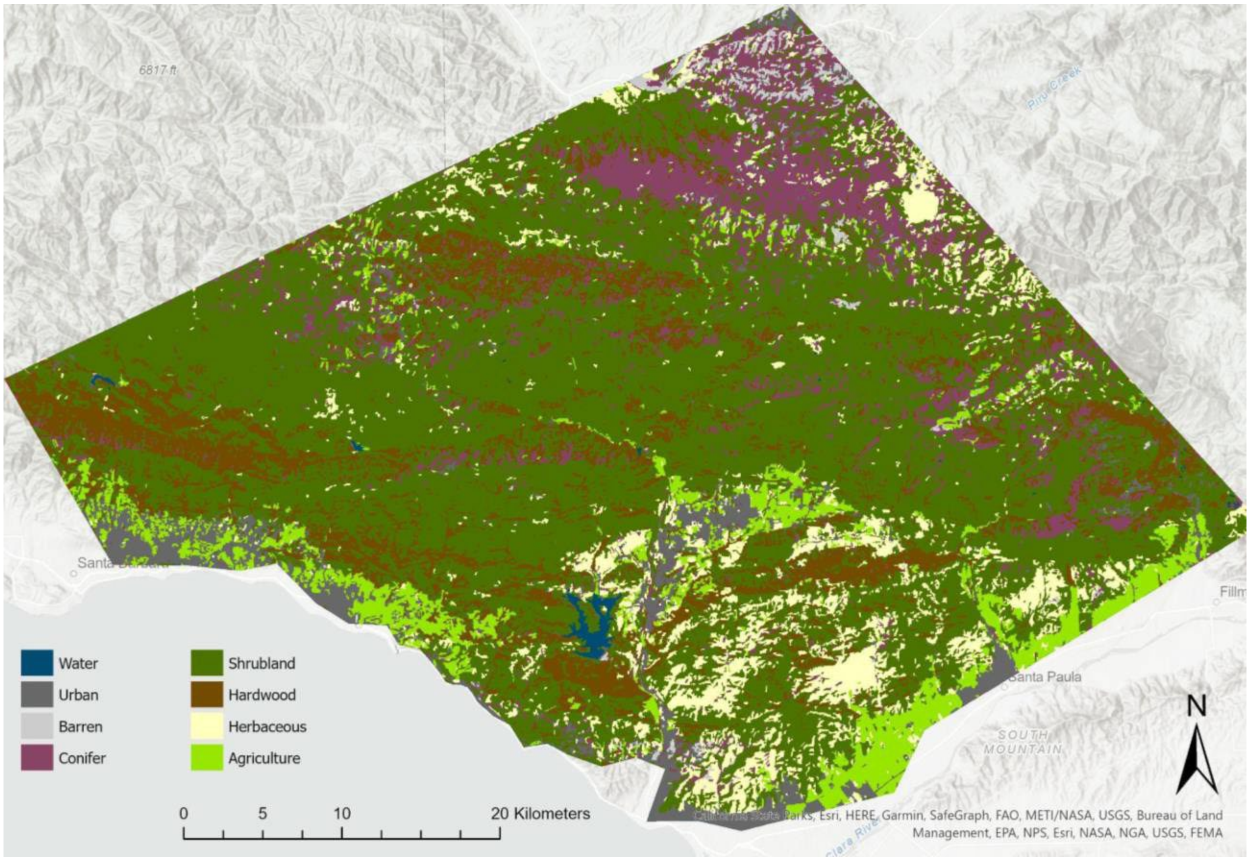
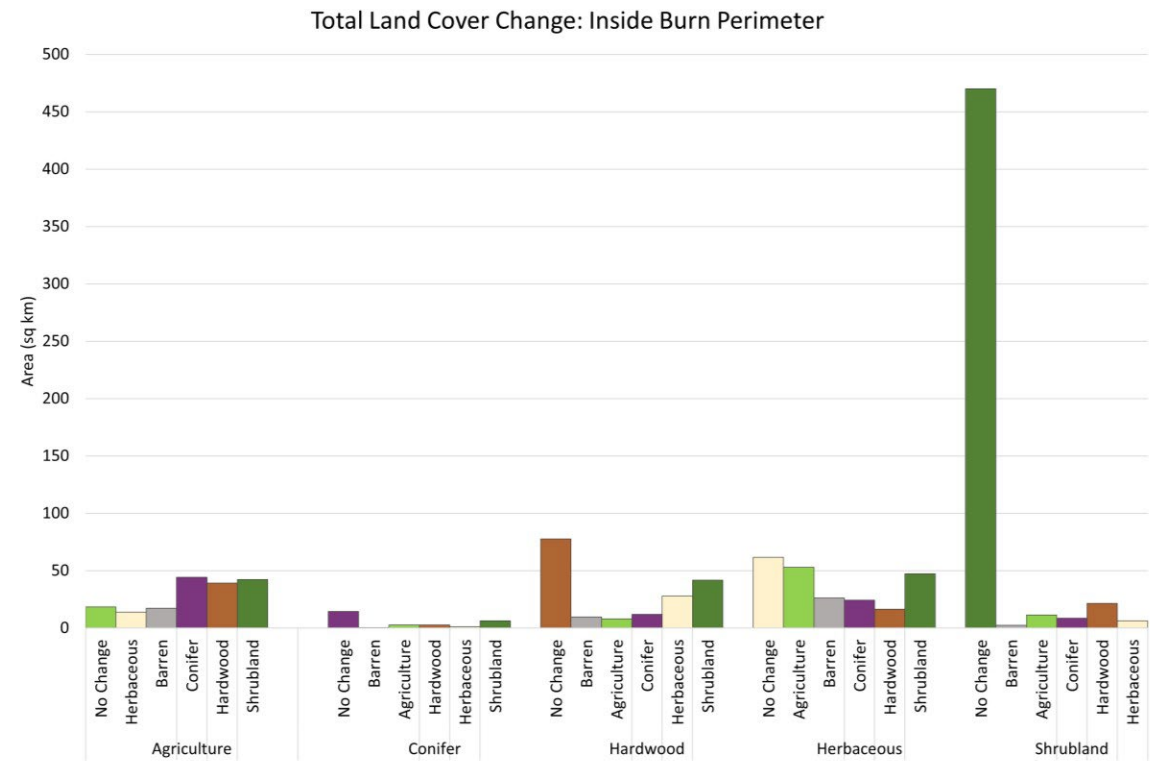


Figure 7. Land cover classification output for September 2022.

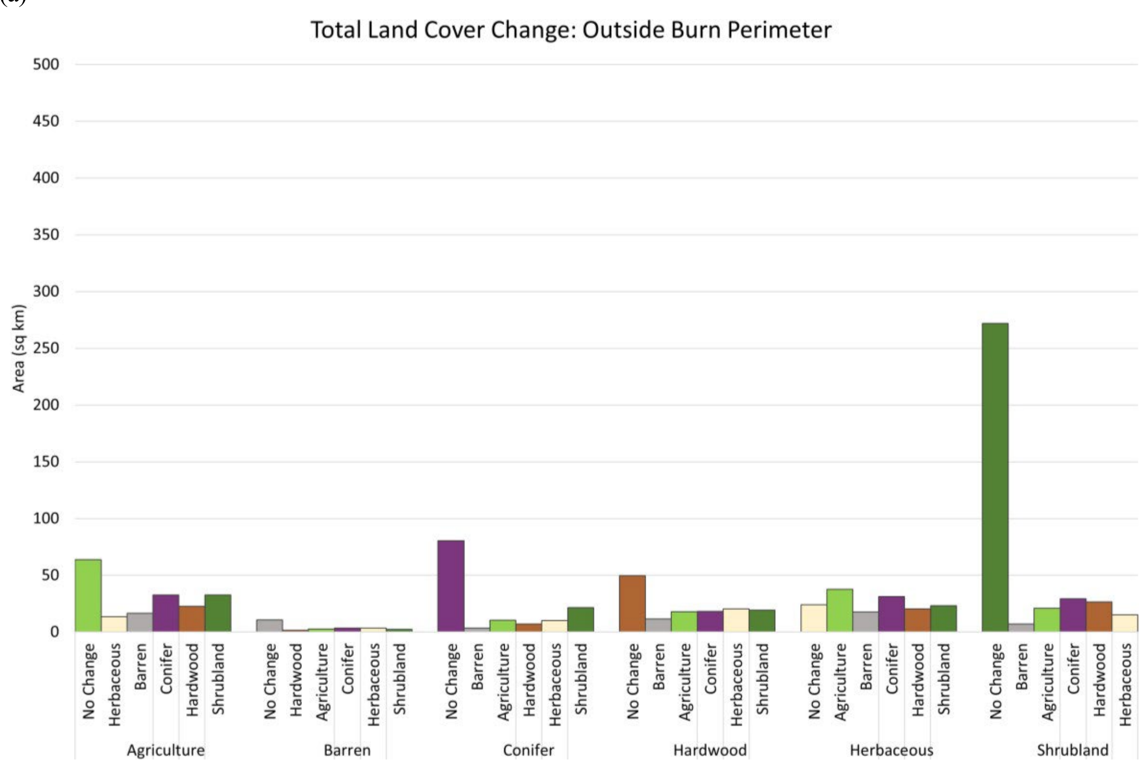
Of the five vegetation classes, the most common type conversions were Herbaceous to Agriculture, Agriculture to Conifer, and Agriculture to Shrubland (Figure 8a). I determined that the areas with the most vegetation change did not occur within the burn perimeter of the Thomas Fire (Figure 8b).

Table 4. Change in proportional land cover area of the six vegetation classes.

Vegetation Type	Total Decrease ($-km^2$)	Total Increase (km^2)	Net Change	Total Area (2015)	% Change
Agriculture	274.44	165.04	-109.40	153.84	-71.12
Barren	16.036	112.17	96.14	34.15	281.52
Conifer	66.43	203.77	137.34	227.51	60.37
Hardwood	186.23	158.40	-27.83	303.91	-9.16
Herbaceous	297.22	112.52	-184.69	227.03	-81.35
Shrubland	148.92	237.37	88.44	1135.15	7.79



(a)



(b)

Figure 8a and 8b. Total area of vegetation change grouped by pre-fire vegetation type. These were the observed type conversions (a) inside and (b) outside of the burn perimeter.

Burn severity analysis

dNBR

I analyzed the entire extent of the Thomas Fire footprint, which burned approximately 1,140 square kilometers. MTBS primarily classified this fire as being moderate severity, with most of the area burned within the 1st, 2nd, and 3rd severity classes (Figure 9). The average dNBR over the entire area was 98 (±127), or predominantly low severity/ mild disturbance but with high variation within the area (Figure 10). When isolating just the fire perimeter, I found that the average dNBR was 185 (± 119), indicating that it was generally a moderate severity fire, with some pockets of high severity within the burn perimeter.

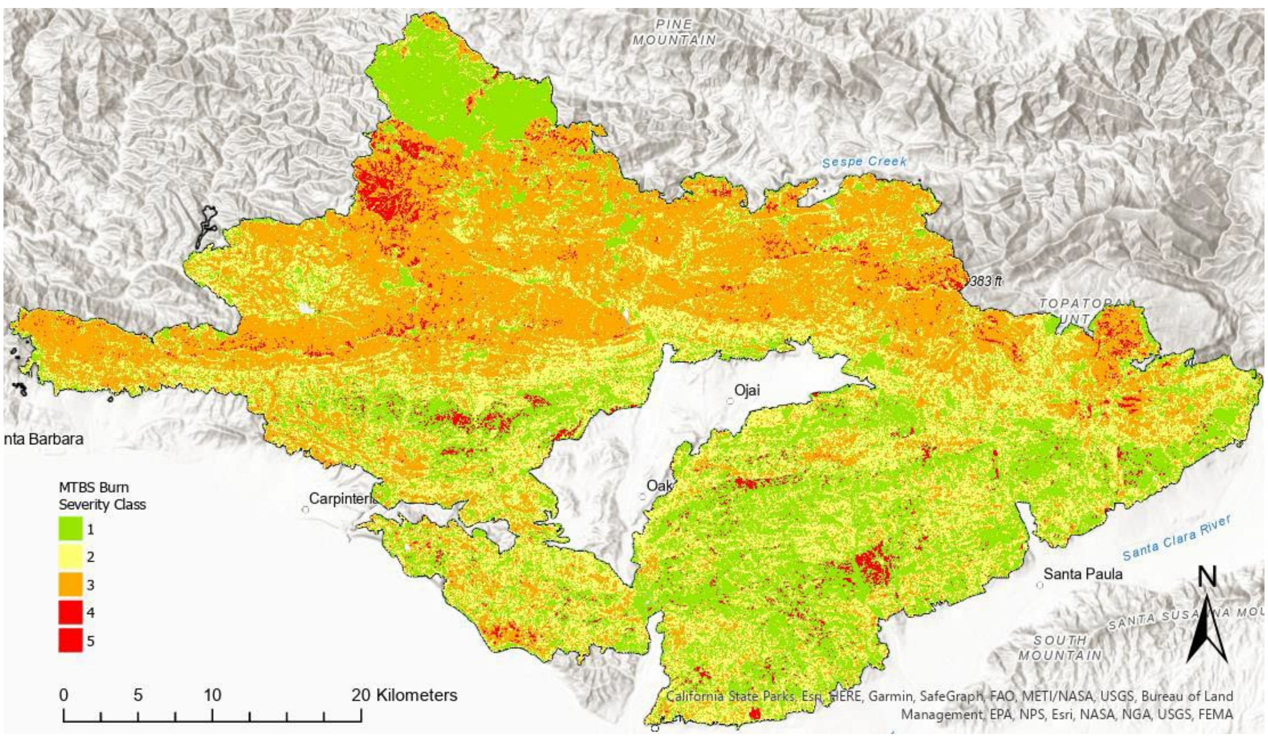


Figure 9. Burn severity classes. From Monitoring Trends in Burn Severity geospatial data.

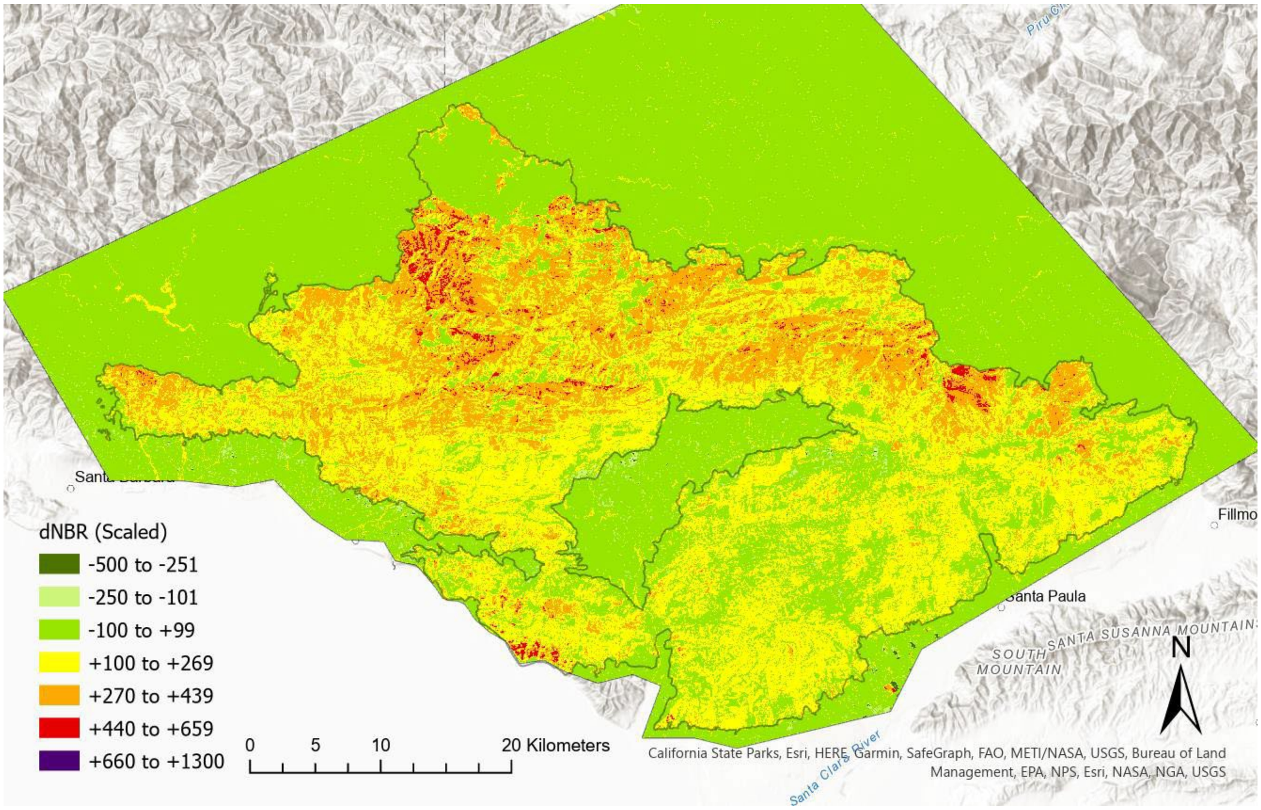


Figure 10. Map of burn severity distribution (dNBR) across the entire study area. Higher values indicate more severely burned areas.

Burn Severity Comparison

When assessing the relationship between dNBR and the MTBS severity classes, I observed that severity classes 1-4 generally fell into their respective designations for the severity classes provided by USGS (Table 5). However, severity class 5 had a much lower average dNBR compared to its respective high severity designation (+660 to +1300). As such, I concluded that areas that were designated a “5” by MTBS had compounding impacts that affected the burn severity in addition to their dNBR value.

Table 5. Comparison of calculated dNBR to MTBS classes.

Class	Minimum	Maximum	Mean	Std. Dev.	90th Percentile
1	-341	525	85.55	78.95	188
2	-315	566	163.10	84.63	274
3	-200	682	271.39	94.82	392
4	-78	647	344.28	105.61	474
5	-308	397	86.29	84.20	183

Comparing burn severity to type conversion

Within the areas that experienced vegetation change, I observed that the majority of low severity fire (1-2) occurred across a relatively even proportional area of all classes (Table 6). Moderate severity (3) primarily occurred in Hardwood, Herbaceous and Agriculture classes while high severity (4-5) fire occurred primarily in the Herbaceous class.

Table 6. Burn severity in type converted areas by pre-fire vegetation type.

Severity Class	Agriculture (km^2)	Conifer (km^2)	Hardwood (km^2)	Herbaceous (km^2)	Shrubland (km^2)
1	77.67	5.58	30.01	84.62	29.18
2	76.70	4.83	38.40	74.53	19.05
3	69.44	7.86	70.40	78.49	22.14
4	3.07	1.70	5.76	4.57	2.01
5	3.37	0.12	0.78	3.68	0.53

Comparatively, I observed that Shrubland had the greatest total area across all severity classes when assessing post-fire vegetation succession (Table 7). The areas classified as being low severity also had a high proportion of Hardwood and Conifer succession, while moderate and high severity classes had a large successional portion of the Conifer class. This could be classification error or a potential restoration of mixed conifer forests in the Northern regions from fire opening previous shrubland that had encroached into the neighboring forest.

Table 7. Burn severity in type converted areas by post-fire vegetation type.

Severity Class	Agriculture (km^2)	Conifer (km^2)	Hardwood (km^2)	Herbaceous (km^2)	Shrubland (km^2)
1	33.99	41.03	43.50	22.05	63.43
2	34.30	38.75	35.66	22.45	58.16
3	38.84	45.35	35.34	26.40	73.89
4	2.76	4.26	1.98	1.61	4.67
5	1.09	1.52	1.31	0.77	2.97

I determined that most of the area fell within burn severity classes 1 through 3, which also had the greatest amount of conversion by area of the five severity classes (Figure 11). Due to their comparatively small size, I grouped severity classes 4 and 5 together for further analysis.

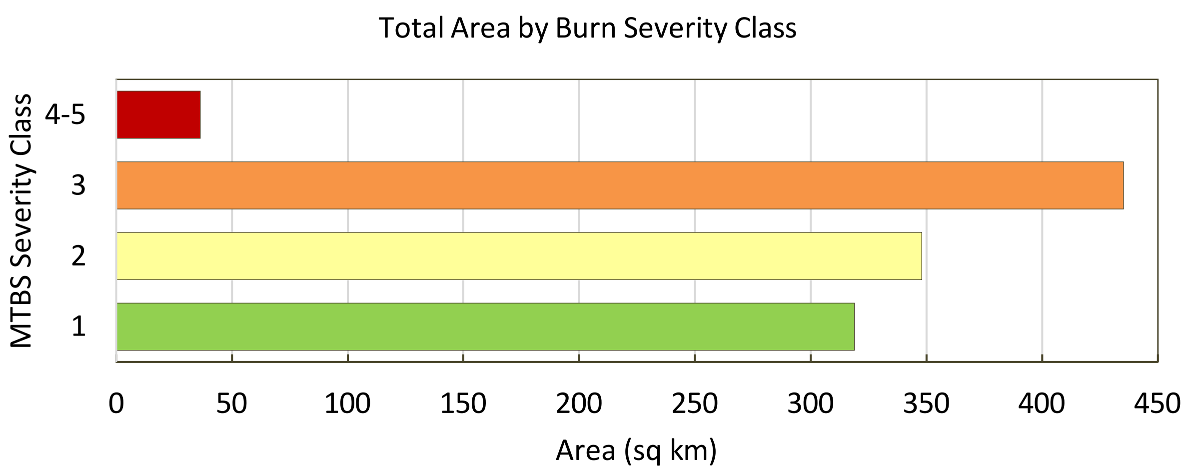
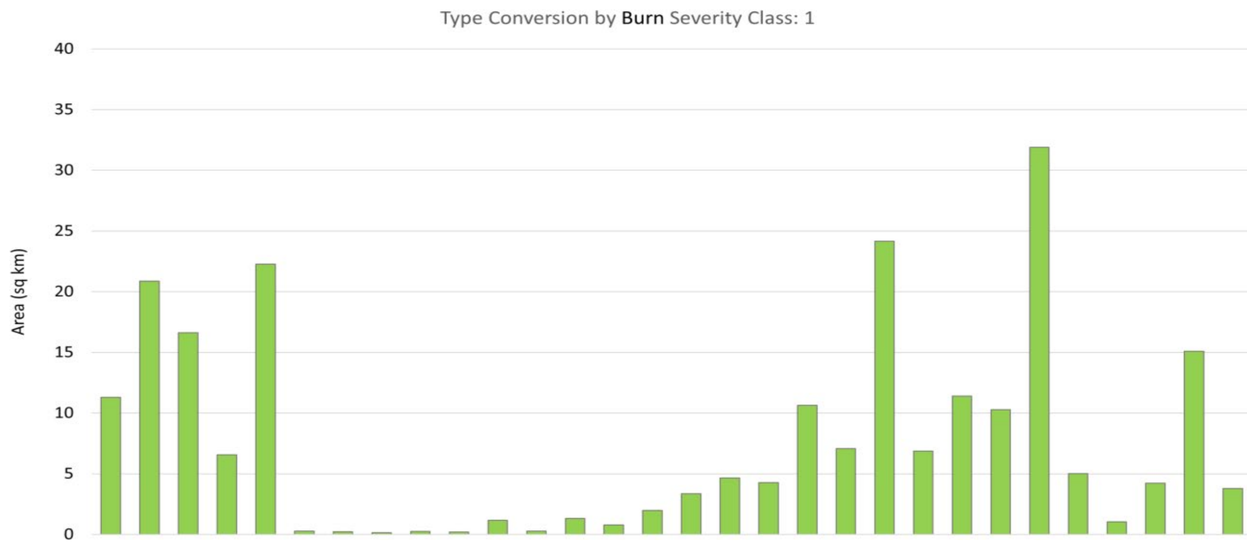
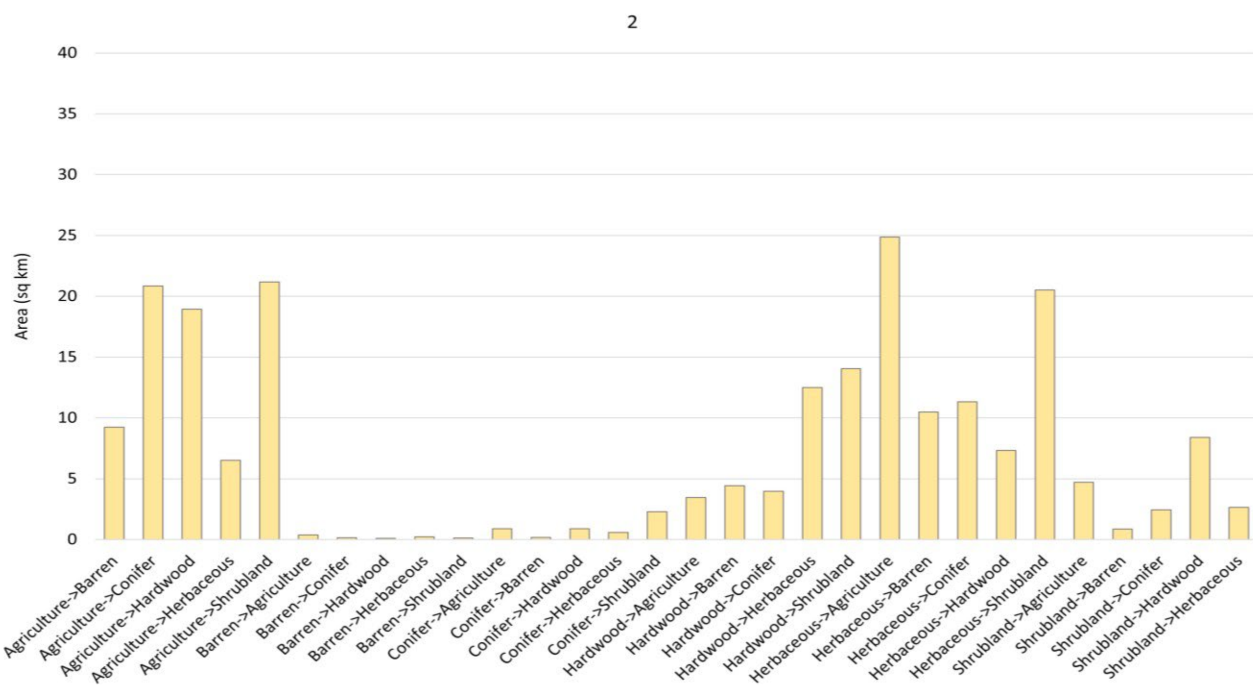


Figure 11. Total area by burn severity class. This is the distribution of severity across the entire fire perimeter.

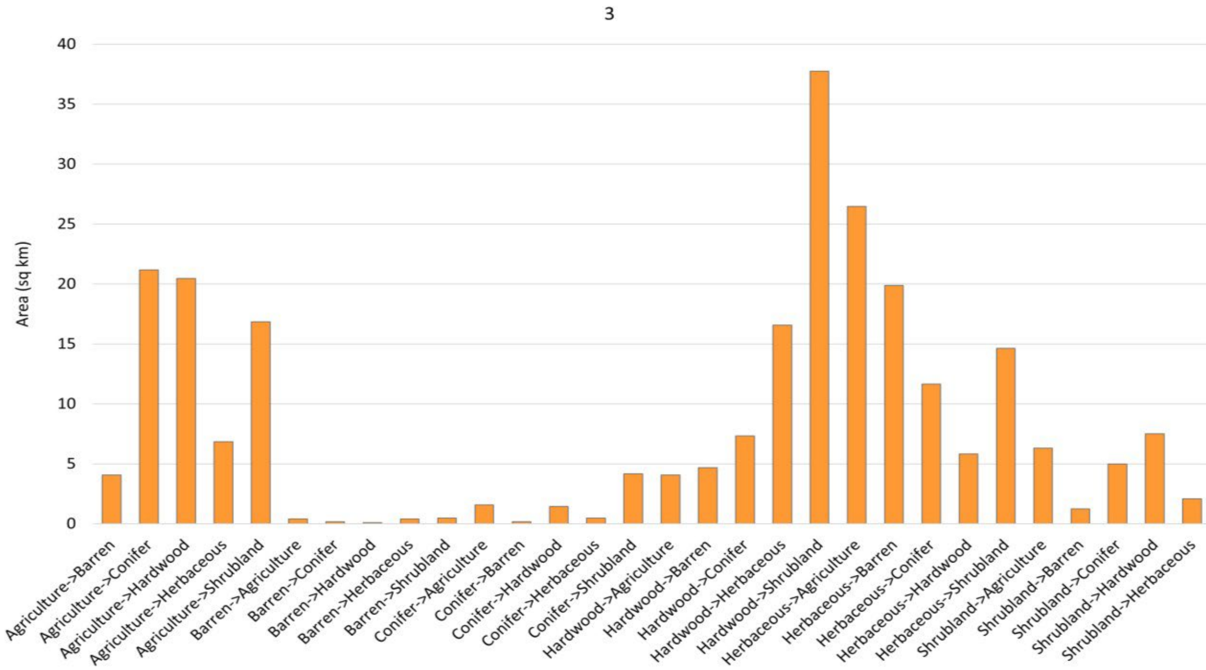
The largest type conversions by area within the burn severity classes were Herbaceous to Shrubland (31.88 km^2), Herbaceous to Agriculture (24.88 km^2), and Hardwood to Shrubland (37.75 km^2) for classes 1, 2, and 3 respectively (Figure 12a-c). I observed that the higher severity classes typically had a more even distribution of conversion across all classes than the lower severity ones, with Herbaceous to Shrubland (2.6 km^2) and Hardwood to Shrubland (2.38 km^2) being the largest conversions by area for classes 4 and 5 (Figure 12d).


Type Conversion by Burn Severity Class: 1
Area (sq km)
0
5
10
15
20
25
30
35
40

(a)

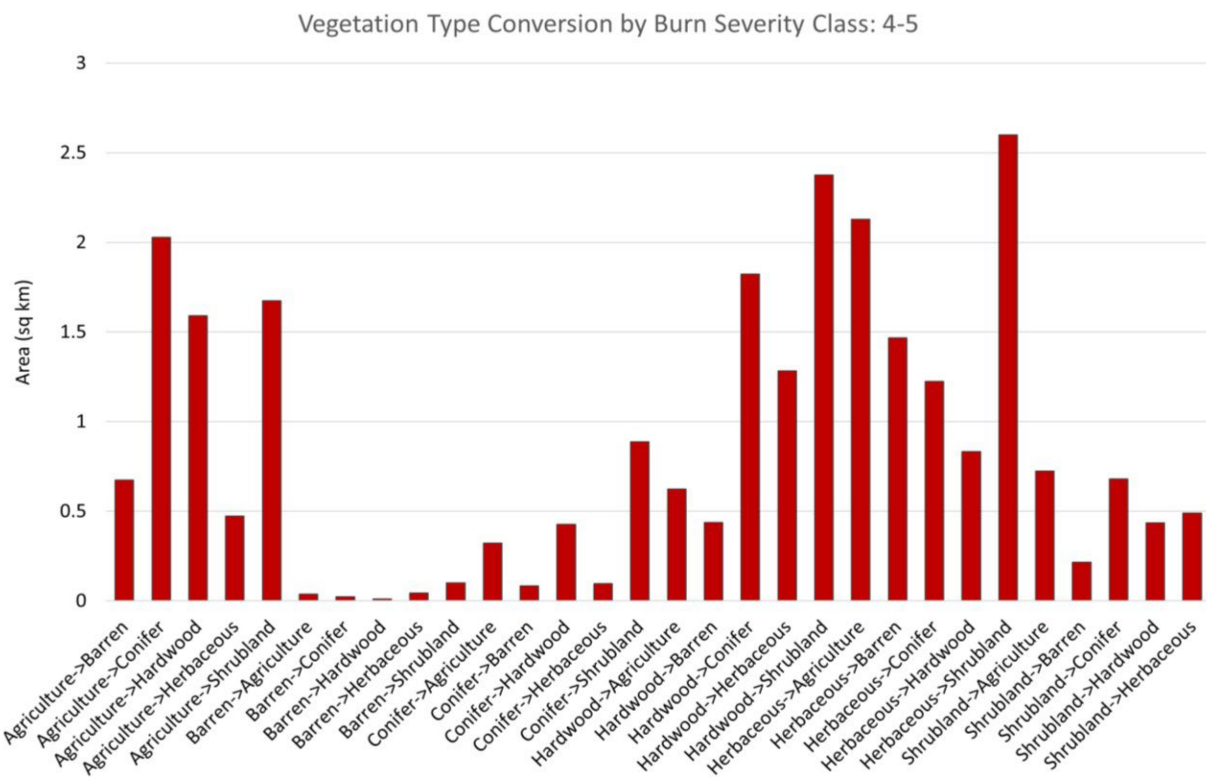

2
Area (sq km)
0
5
10
15
20
25
30
35
40
Agriculture->Barren
Agriculture->Conifer
Agriculture->Hardwood
Agriculture->Herbaceous
Agriculture->Shrubland
Barren->Agriculture
Barren->Conifer
Barren->Hardwood
Barren->Herbaceous
Barren->Shrubland
Conifer->Agriculture
Conifer->Barren
Conifer->Hardwood
Conifer->Herbaceous
Conifer->Shrubland
Hardwood->Agriculture
Hardwood->Barren
Hardwood->Conifer
Hardwood->Herbaceous
Hardwood->Shrubland
Herbaceous->Agriculture
Herbaceous->Barren
Herbaceous->Conifer
Herbaceous->Hardwood
Herbaceous->Shrubland
Shrubland->Agriculture
Shrubland->Barren
Shrubland->Conifer
Shrubland->Hardwood
Shrubland->Herbaceous

(b)



(c)

Figure 12a, 12b, and 12c. Type conversions in each burn severity class. The first three classes had the greatest total area burned, and the distribution of the respective class conversions was contingent upon the severity class.



(d)

Figure 12d. Type conversions by area for severity classes 4 and 5. The two highest severity classes had a much smaller total area burned than classes 1-3.

DISCUSSION

I found that there was a shift in both the overall distribution and mean dNDVI between the study years, from 0.0 in 2015 to -0.05 in 2022, suggesting a potential change in both the extent and types of vegetation within the study area. The classification schema I used to compare vegetation in 2015 and 2022 was 68% accurate with an overall agreement between producer and user accuracy of 57%. To identify burn severity, I looked at the entire extent of the Thomas Fire and found that most of the area burned was within the first three severity classes, which was validated by a mean dNBR of 185 (± 119), corresponding to a low to moderate severity fire overall. Across the entire study area, I did not find a higher proportion of type conversion within the burn perimeter, indicating that there might have been other factors (drought, land use change, climatic shifts) that were driving the change in vegetation type instead. When comparing type conversion classes to area burned, there was not a proportionally larger amount of change in the higher burn severity classes, further supporting the idea that more severe fire was not the key factor in causing type conversion.

Vegetation change

In the early successional stages of chaparral shrubland after a disturbance, it can be difficult to accurately distinguish different vegetation types from one another. Accurate classification can be crucial to determine how and to what extent vegetation community composition might be changing (Guo et al. 2001, Tiribelli et al. 2018, Keeley et al. 2022). The supervised classification schema used to determine the land cover types for the 2015 data returned an overall accuracy of 68%, suggesting that it was somewhat accurate in determining the extent of land cover change due to the Thomas Fire. The utilization of broader life form categories allowed me to gain some insight into the larger regionwide vegetation dynamics without requiring high spectral resolution. The extent and explicit spatial location of vegetation change is important for management decisions regarding the balance between biodiversity and community safety. For example, chaparral to herbaceous type conversion does not post a large fire hazard in more remote areas, but a lot of chaparral shrubland is close to the WUI and as such, may pose a greater risk to communities if type conversion takes place (Syphard et al. 2011). Conversion to herbaceous annual cover is problematic in these areas as the annual resprouting habit and seasonal desiccation in the warmer dry months poses a greater likelihood of reburns, which can increase community smoke exposure in populated areas.

Regardless of the extent of vegetation change, determining the effect of more frequent and high severity fires on vegetation succession in shrubland is important for future management decisions (North et al. 2012). Some vegetation change was detected, supporting empirical evidence that suggests fire severity can lead to type conversion (Conard and Weise 1998, Syphard et al. 2021). However, there was not a significantly higher proportion of type conversion from shrubland to grassland within the burn perimeter compared to outside. This provides inconclusive evidence as to the extent of this specific fire's impact on chaparral type conversion, especially considering most of the area classified as shrubland in 2015 remained unchanged in 2022. Even though chaparral ecosystems are characteristically resilient to infrequent, high severity fire, we are now seeing an increase in the frequency as well as severity of uncontrolled wildfires. This is compounded by drought conditions that continued after the fire, leading to more typically resilient species to be compromised (Dong et al. 2019, Field et al. 2020, Keeley et al. 2022). Current management practices still err on the side of suppression in chaparral shrubland, as historical fire regimes that were supported by Indigenous burning are difficult to replicate. Additionally, metrics that indicate "healthy chaparral" might fail to meet other management goals (North et al. 2012).

Burn severity

I found that most of the area burned in the Thomas Fire was classified as low to moderate severity, although this is relative given the ecology of the study site. dNBR is one standard metric used for remotely calculating burn severity, although lower reflectance vegetation cover such as shrubland typically exhibits less of a spectral signal, and as such is a less robust application of the metric (Szpakowski and Jensen 2019, Storey et al. 2020). More delineated spectral signals tend to show up in forested ecosystems in comparison to more homogenous landscapes such as chaparral shrubland, so using a standardized metric such as the categorical burn severity data allowed me to compare the Thomas Fire on a standardized scale to other wildfires. The categorical data from MTBS considers dNBR (differenced Normalized Burn Ratio) and other factors such as impacts on soil moisture and vegetation mortality after a fire (MTBS 2022). This supported the dNBR data that suggested low to moderate severity overall, despite the large spatial extent and community disruption that accompanied this disturbance (Syphard et al. 2021). Additionally, the vegetation classes with higher spectral reflectance (Conifer and Hardwood) were more likely to be categorized as moderate severity as opposed to low, which could have reflected higher mortality and conversion within the burn perimeter of those classes, or simply a measurement of flame intensity due to higher fuel loads in more forested regions.

Comparison of burn severity to type conversion

The burned and unburned areas of the study site had a very similar proportion of vegetation change among the five classes. The Shrubland class remained the largest by area and experienced very little type conversion proportional to the total area. The Hardwood class experienced a similar amount of change in all classes outside of the burn perimeter, but a much higher proportion of Shrubland and Herbaceous type conversion within the perimeter. This supports other literature that suggests that high severity wildfire can cause type conversion in ecosystems with historically low severity, more frequent fire regimes, or those less adapted to high severity fire (Steel et al. 2015). The fact that chaparral had very little type conversion supports other studies that have asserted that fire return interval, not overall severity, drives shrub mortality and type conversion (Hope and Clark 2007, Meng et al. 2014, Conard and Weise 2015).

The higher burn severity class (4-5) experienced a proportionally greater incidence of type conversion to Shrubland in almost all classes, but especially for the Hardwood and Herbaceous classes (Figure 11d). This suggests that for those classes, high burn severity did have a significant impact on the type conversion that took place, even if it was overall a very small amount by area. Drought coupled with high severity wildfire drives extensive tree mortality, so this finding supports other studies conducted in different forested ecosystems (Steel et al. 2015, Field et al. 2020). In comparison, the lower severity classes (1-3) had a much more even distribution of vegetation change across all classes. This suggests that other factors (including inconsistencies in my classification schema) were causing type conversion, and not necessarily the burn severity in those instances.

Limitations

The spatial (30m) and temporal scales of available geospatial data limited the number of inferences I could draw about community- level type conversion dynamics. Using a smaller spatial resolution sensor would likely yield more accurate classification results as well as provide a more in-depth view of how vegetation changed over time, potentially identifying vegetation to more specific communities (such as coastal sage scrub versus just shrubland). This could also eradicate errors such as misclassifying herbaceous cover to agriculture, which likely caused inconsistencies in the results (e.g., the high conversion to the Agriculture class). I did not investigate what management and agricultural practices have taken place in the years following the Thomas Fire, which would have likely informed more accurate analysis of the data that I collected.

A considerable limitation of this study is that it only follows the changes 5 years after the Thomas Fire, and as such still falls under the earliest phases of full shrub succession following a disturbance. As it is, life-form level vegetation type conversion is not completely indicative of significant change, especially considering that primary succession of shrubs immediately following fire can mimic the spectral signature of herbaceous or grass cover (Guo 2001).

Future directions

In the future, longer temporal analyses of the effects of fire on community level vegetation succession dynamics should continue to be monitored in chaparral. Since the historical fire regime is typically infrequent and high severity, this wildfire event may not have fallen outside of the typical regime that this chaparral ecosystem is accustomed to, thereby having relatively small impacts on the overall successional processes that are activated by disturbance. Ongoing monitoring should take place within the burn perimeter to see if this vegetation conversion establishes long term. Regardless, it is of utmost importance that we continue to assess the impacts of large scale, high severity wildfires to both ensure community safety as well as preserve biodiversity in the face of future disturbance.

Broader implications

It is worth noting that treating fire as an unmanageable environmental inevitability is a rather recent cultural belief, brought about by the timber industry in the early 20th century. Prior to that, Indigenous land management practices such as cultural burning were used to generate specific land cover types to support species of interest. Therefore, when discussing active ecological management to reduce fire severity, the management goals that we approach chaparral shrubland with in the modern era need to be adapted appropriately. This can be accomplished by balancing the needs of ecosystems to support biodiversity and adequate habitat cover, modern recreation, and agricultural practices. Additionally, consulting Indigenous communities in our management decisions (especially when pertaining to fire) should be integral to the study of ecology and land management.

The results found in this study add to the broader understanding of ecoregion level vegetation dynamics, and support other studies that consider more frequent fire and compounding natural disturbances as the driving forces behind type conversion in chaparral. Management decisions surrounding ecosystems with infrequent, high severity fire regimes face unique challenges as fire suppression becomes the necessary management strategy to replicate historical fire regime conditions. Other areas, such as frequent fire adapted conifer forests, will benefit from fuel treatments such as thinning and a reintroduction of prescribed fire, but the same cannot be said for Southern California chaparral. Fuel loads are not necessarily out of historical levels for chaparral shrubland, but the proximity to the Wildland Urban Interface does necessitate discussion about the prevention of wildfire to protect communities. As such, new management strategies (such as creating fuel breaks and leaving large continuous stands intact) must be implemented to preserve this natural biodiversity as well as prevent further large-scale disasters from occurring.

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