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Post Wildfire Vegetation Response to the Wildland-Urban Interface: A Case Study of the Station Fire

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Abstract

In the past, wildfires served as a method for mother nature to promote biodiversity and to help maintain a functioning ecosystem. However, climate change alters the fire regime, significantly impacting vegetation recovery. Human disturbances and increased land use and land cover heighten vegetation disruption and abundance after a fire. Wildland-urban interface (WUI) – the region where the vegetation intermingles with the roads, houses, and human-made structures – threatens vegetation and the human population. Overall vegetation recovery after the Station Fire of 2009 spread through the San Gabriel Mountains, Los Angeles County was observed using Digital Elevation Model (DEM), Normalized Difference Vegetation Index (NDVI), and Normalized Difference Burn Ratio (nDBR) spectral indices. In addition, Light Detection and Ranging (LiDAR) images were used to measure aboveground biomass (AGB). The study analyzed vegetation biomass recovery by comparing human disturbances and the level of fire severity within the Station Fire perimeter. Low and moderate fire severity were compared in detail against WUI and non-WUI regions by quantifying the amount of biomass in the specified regions. Linear regression model results showed vegetation recovery rates were slower in WUI regions than in non-WUI regions despite having similar regeneration patterns while AGB rebound was similar across both region categories.

Introduction

Wildfires are important natural disturbances that help maintain the equilibrium of chaparral ecosystems. Fire can rid the natural ground cover of diseases and nourish the soil. Natural fire regimes facilitate the recovery of certain vegetation types. The disruptions in the environment caused by wildfires can provide a quick opportunity for environmental renewal. However, anthropogenic factors such as climate change-induced extreme fire hazard weather patterns, human-related ignition sources, and land abandonment practices have all increased the prevalence and the risk of uncontrolled fires (Martín-Alcón et al., 2015). Wildfire amplification results in vegetation loss, soil disturbance, and a reduction in biological activity (Efthimiou et al., 2020).

In the chaparral ecosystem, biomass can be rapidly replenished by long-interval fires. A typical chaparral landscape is shrub-dominated and is usually found at medium elevations. After a wildfire, the chaparral shrubland will promote seed production to stimulate rapid regeneration. The resilience of this vegetation type enables it to flourish after a wildfire. There is only one caveat: if there are repeated or multiple fires over short periods at the same site, the chaparral will not be able to adapt and regenerate (Storey et al., 2021). A change in fire intensity or frequency can thus profoundly impact the chaparral ecosystem's structure and composition over time (Barro & Conrad, 1991). For example, increased wildfire frequency or variation, can reduce seed dormancy periods and promote seed mortality.

Aside from wildfires, human disturbances also play a vital role in reducing vegetation biomass. The expansion of urban sprawl over recent decades has led to the intensification of the wildland-urban interface (WUI), which has severely impacted chaparral ecosystems. The WUI region refers to areas in which human-made structures intermingle with wild vegetation and increased human activity in WUI regions can greatly exacerbate the fire risk (Syphard et al., 2021). Human disturbances can be classified in various ways, including recreational activities, consumptive and non-consumptive activities like camping, off-roading, gardening, cooking, casual outdoor activities, picnicking, and hiking. Human disturbances also refer to aspects of the built environment, such as buildings and roads. The expansion of the WUI puts not only the chaparral ecosystems at risk, but the human-made infrastructure at risk as well.

With an ever-growing population, buildings and infrastructure construction programs will continue to expand. As a result, there is an amplified interaction between humans and the environment in both WUI and non-WUI areas. It is no coincidence that wildfires in Southern California are estimated to be rising exponentially in frequency and intensity. It is also noteworthy that human activities are major factors in the decline of vegetation rebound capacities, especially in high-mountainous locations (Rull et al., 2011). Human-induced climate change, and human impacts on land cover and land use, all negatively impact the chaparral and similar vegetation types in California. As a result of climate change, droughts are increasing, slowing down vegetation growth.

Surface topography is another significant factor affecting vegetation recovery. There is a particular pattern of burning that intensifies and lengthens wildfires due to elevation, aspect, and soil type (Keeley & Safford, 2016). Wildfires in elevated zones and sloped areas change soil properties, including permeability (Efthimiou et al., 2020). As a result, the soil becomes hydrophobic, reducing soil absorption and creating an inhabitable layer for vegetation. Thus, repeated burnings and human disturbances in higher elevation and steeper slope areas particularly impede natural vegetative recovery.

Satellite-based monitoring technologies can now be used to accurately quantify vegetation biomass. The Normalized Difference Vegetation Index (NDVI) and Normalized Difference Burn Ratio (nDBR), both generated from remote sensing imagery, can delineate fire patterns, characterize burn severity, and identify changes in vegetation structure (McCarley et al., 2017; Wulder et al., 2009). Satellite-based monitoring quantifies NDVI to approximate vegetation biomass, crown and canopy cover, vegetation density, and vegetation health. Satellite-based imagery from Landsat and Sentinel-2 are popularly used to capture high-resolution images to calculate NDVI. Basically, NDVI estimates vegetation by measuring the difference between the near-infrared and red wavelengths of the electromagnetic spectrum. Vegetation strongly reflects near-infrared while absorbing red wavelength in contrast. A potential indicator of burn severity could be used to manage the functionality of a given burned area as a measure of ecosystem rehabilitation. Similar to NDVI, the nDBR spectral index identifies the burned areas of the vegetation. The ratio between the near-infrared and short-wave infrared wavelengths are used to calculate the nDBR of a given area. The nDBR estimates the burn severity of a targeted area to specify severe vegetation damage or regrowth post-wildfire.

Three-dimensional remote sensing models such as Light Detection and Ranging (LiDAR) are other beneficial tools for digitally modelling vegetation biomass. LiDAR is an active remote sensing tool that utilizes sensors and returned pulses to categorize various classified points such as ground level, low, medium, or high vegetation. It involves mounting a laser instrument on a low-flying aircraft that emits pulses of light that reflect off of objects and then back to the sensor. LiDAR is an accurate tool for reconstructing, recreating, and measuring three-dimensional vegetation structures (Guo et al., 2017). LiDAR has thus emerged as a powerful tool for characterizing post-disturbance regeneration assessments to accurately characterize vegetation attributes (Martín-Alcón et al., 2015).

Two major concerns that pose a threat to vegetation biomass post-wildfire are short-interval fires and human disturbances. Daily recreational activities and fuel sources provided by humans can increase fire risk and fire prevalence. Short-interval fires and repeated burning at the same locations can severely impact the topography of the land, fire regime, and soil regime. However, it remains unknown the degree to which short-interval fires destroy or inhibit overall vegetation biomass regrowth. This study aimed to explore the recovery of vegetation biomass post-wildfire in the presence of human activity in a WUI area outside Los Angeles, California. It focused on addressing the question of whether wildfires and the WUI play a ubiquitous role in limiting post-wildfire vegetation recovery. Taking a broader, landscape-wide approach, the objectives of the study were to (1) explore visual accounts of the land cover and land use in the WUI and non-WUI regions based on the elevation and the spectral indices such as NDVI and nDBR and (2) analyze the linear relationship of biomass regeneration and examine above-ground biomass (AGB) by observing the relationship between the WUI and non-WUI region and the level of fire severity such as low and moderate fire severity.

Methods

Study Area

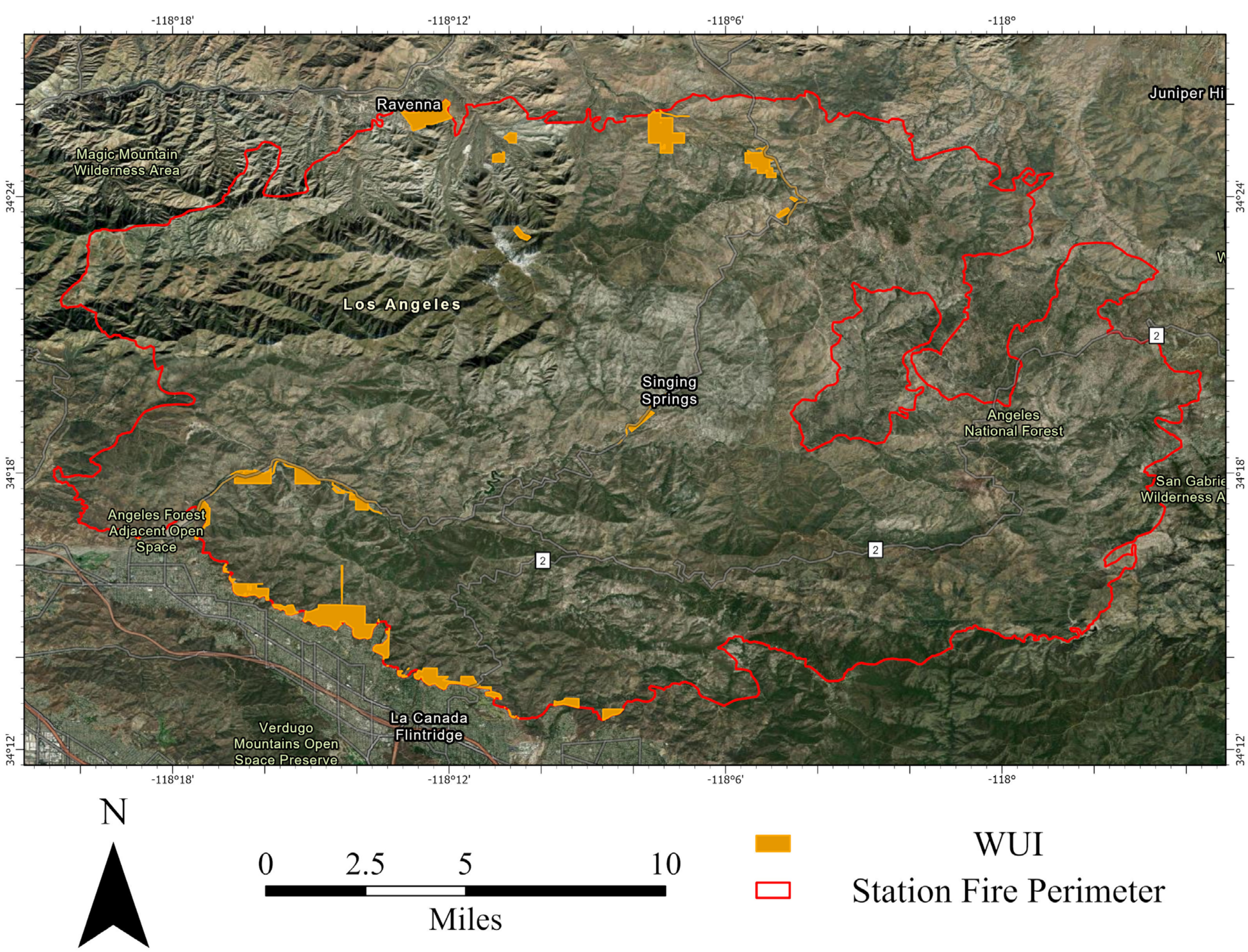
This study was conducted in the San Gabriel Mountains of Los Angeles County, focusing on a tract that extends from 34°18'49" to 34°19'34" North and 118°8'14" to 117°56'14" West (figure 1). The Station Fire was one of the largest wildfires in California that combusted 160,557 acres of land. The Station Fire was first recognized on the 25th of August 2009, and was not contained until almost two months later on the 16th of October. Prior to the wildfire, chaparral was the most dominant vegetation type in this region, covering 75% of the total surface of the perimeter. Other vegetation types such as conifers, oaks, and other hardwoods, as well as desert shrub were also present in the study area. Within this part of the Angeles National Forest, slopes ranged between 20% and 60%, with elevations ranging from 397 to 2432 meters above sea level (m asl) (Thompson et al., 2021). Prior to the Station Fire, the vegetation of the area did not experience any significant fire activity in the previous 40 years, which created a prominent fuel source for when the 2009 fire began. Moreover, the absence of significant winds and drought stress exacerbated the vulnerability of the fire. The perimeter of the fire is shown in figure 1 (Holtzclaw, 2021).

Field Methods and Data Acquisition

The study focused on elevation variations and on spectral indices such as the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Burn Ratio (nDBR). Visual predictor models were created to evaluate the initial hypothesis that the expanding WUI region and/or human disturbances have negatively influenced post-wildfire regeneration. Figure 1 demonstrates how WUI areas have expanded into the study region along the northern and the southwestern peripheries of the Station Fire perimeter, plus near the Big Tujunga Creek in the southwest portion of the study area.

Figure 1

Location, study area, burn perimeter, and wildland-urban interface of the 2009 Station Fire.



Topography and Hydrology

Elevation data were obtained from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (90 m, spatial resolution) dataset (Peterman, 2013). Major rivers and streams were retrieved from the National Hydrology Dataset (n.d.). Historical fire perimeters were acquired from the California Department of Forestry and Fire Protection's Fire and Resource Assessment Program (FRAP) Fire Perimeters dataset (FRAP, 2021).

Wildland-Urban Interface (WUI)

The WUI data were acquired from the Spatial Analysis for Conservation and Sustainability (SILVIS) Lab at the University of Wisconsin-Madison (Gilbert, 2019). The WUI was defined as the area of intermix where man-made structures are built near or among lands prone to wildfire. The expansion of the WUI region directly introduces more human activity into areas that were formerly characterized as pure wildland. It is important to note that the expanded WUI does not include any attendant increases in responsible environmental preservation or conservation policies, which ended up decreasing the amount of defensible space and increasing the spread of wildfires. The urban sprawl in WUI areas has also led to the increase in wildfire prevalence in California.

Normalized Difference Vegetation Index (NDVI)

The NDVI is a technique to measure health, greenness, and vegetation abundance. NDVI pre-fire and post-fire conditions were used to calculate the greenness of the dominant vegetation. NDVI was calculated using Landsat 5 Thematic Mapper (TM+) images obtained from the United State Geological Survey (USGS). The satellite images retrieved for the study were captured on July 7 and October 25, 2009. The NDVI index ranged from -1 to 1. Large negative values indicated unhealthy vegetation, sparse vegetation, or dead vegetation. Large positive values indicated abundant, green, and healthy vegetation. Sometimes, obstructive clouds, snow, ice, or water can interfere with NDVI values. In some cases, an NDVI value of 0 revealed inorganic objects in the WUI such as human-made structures. To calculate the NDVI, formula 1 (below) was used, which takes near-infrared (NIR) and visible red bands, and divides them by their sum (Levin, 2019):

Formula 1:

$$\text{NDVI} = \frac{\text{NIR - RED}}{\text{NIR + RED}}$$

Normalized Difference Burn Ratio (nDBR)

Pre-fire and post-fire images were used to calculate the nDBR for the overall study area. The nDBR data were acquired from the USGS Landsat 5 TM+ imagery from July 7 to October 25, 2009. The Difference Burn Ratio (DBR) (formula 2) was applied to the before and after fire satellite images to calculate the ratio between NIR and shortwave-infrared wavelengths (SWIR) of the electromagnetic spectrum. After calculating the DBR, the nDBR was measured by the ratio between the pre-fire DBR and post-DBR (formula 3). Remotely sensed images were paired before and after the fire to determine the loss of vegetation biomass caused by fire. Char depth, reduced infiltration, loss of organic matter, changes in structure and phenotypic color, and the effects of fire on the ground surface were considered (Eidenshink et al., 2007).

Formula 2:

$$\text{DBR} = \frac{\text{(NIR - SWIR)}}{\text{(NIR + SWIR)}}$$

Formula 3:

$$\text{nDBR} = \text{PreFireDBR - PostFireDBR}$$

Large negative values indicated post-fire regrowth, whereas large positive values signified strongly burned areas with no post-fire regrowth. To define the nDBR values extracted as seen in formula 2 and formula 3, fire severity categories including "unchanged," "low fire severity," "moderate fire severity," and "high fire severity," were derived from a Composite Burn Index (CBI) (Miller & Thode, 2007). The relative index was chosen because of the heterogeneous composition of vegetation in the Station Fire perimeter. The thresholds of the relative index had greater accuracies than ecosystems with homogenous compositions. CBI was calculated by assigning values to the fire effects on the vegetation strata. During the evaluation process, fire effects such as char height, species mortality, and soil and composition changes were also taken into account, as well as vegetation strata like substrate, herbs, shrubs, and trees. After assigning threshold values to burn severity categories, the severity levels were determined.

Light Detection and Ranging (LiDAR) Data

LiDAR data in point cloud format were obtained from two free online databases: 2009 LiDAR data from Open Topography and 2016 LiDAR data from the USGS. LiDAR point returns were classified into the following categories: Unclassified, Ground, Low Vegetation, Medium Vegetation, High Vegetation, Building, Low Points, and Reserved, by using the Gaussian smoothing kernel to accurately find the apex of the vegetation for high frequency spatial filtering. The height or vertical filtering classified LiDAR points based on feature extractions using elevation, intensity, and echo times of the returned pulses. LiDAR data were processed using the vertical accuracy assessment to evaluate vegetated and non-vegetated areas.

Above-Ground Biomass

The model sampled 80 plots measured at 30 x 30 m2 across the Station Fire Burn Perimeter. Every plot in the WUI and non-WUI regions was approximated for the above-ground biomass (AGB) using the given LiDAR data. Above-ground biomass was defined as all living material above the Earth's surface layer expressed as kg/m2. The AGB was quantified using a random selection of predictors and samples from training data to measure ground truth biomass (Schrader-Patton & Underwood, 2021). The Digital Terrain Model (DTM), Digital Surface Model (DSM), and Canopy Height Model (CSM) were extracted from the LiDAR data. The DTM represented the bare ground and delineated the watersheds in the plot. The DSM analyzed the top of the vegetation canopy. The CSM was the difference between the DSM and CSM that provided the canopy height. Then, it was converted by the allometric equations from the Random Forest model to compute the AGB. The biomass allometric equation was applied to obtain a ground truth biomass as seen in formula 4. Where, B is biomass (kg/m2), H is height (m), C is cover (%), and BD is bulk density (kg/m3).

Formula 4: $$B = H \times C \times BD$$

The Random Forest Algorithm was implemented with the predictor biomass values to extract the ground truth biomass values to improve the accuracy. To avoid overestimation or underestimation of biomass, the forest regression model was used to accurately calculate the vegetation biomass in the WUI and non-WUI regions from the predictors. The output was the total above-ground biomass given in kilograms for the vegetation cover area sample plots.

Statistical Analysis

To assess if WUI regions contained different means of above-ground biomass (AGB) than non-WUI regions, a two-sample independent t-test was conducted for the 2009 and 2016 LiDAR data. Twenty plot samples for each region were tested to differentiate the AGB means (n = 40). Plots were chosen using convenience sampling to conduct respective analyses. Simple linear regression models were performed to quantify vegetation recovery rates in WUI and non-WUI regions. The study sampled 20 plots for each region to obtain the linear regression equation. The degree of fire severity and the type of region were also analyzed using a two-way ANOVA (2 x 2 factorial design) to see if there was a significant difference in AGB means between these two variables, and to determine if fire severity did not impact the type of region. The study sampled 10 plots for each condition: WUI and moderate fire severity, WUI and low fire severity, non-WUI and moderate fire severity, and non-WUI and low fire severity (n = 40).

Results

The digital elevation models demonstrated that elevation impacted vegetation structure, composition, and recovery in the WUI and non-WUI regions. The Station Fire elevation map displayed WUI areas in the Northern regions (600 m asl on average), Southwestern regions (500 m asl), and adjacent to the Big Tujunga Rivers (500 m asl) (figure 2). Within the Station Fire perimeter, there was a clear spatial relationship between the WUI regions and elevation. WUIs were more likely to occur in lower elevations and flatter topography.

Compared to WUI areas, non-WUI regions were spread across a wider range of elevations from 397 m asl to 2432 m asl. Non-WUI areas were dominated by natural vegetation without the presence of roads, houses, and buildings. On another note, some non-WUI regions were near major rivers and streams such as the Pacoima Wash, the West Fork San Gabriel River, the Santa Clara River, and the Mill Creek (figure 2). Therefore, non-WUI regions have ideal growth conditions for natural vegetation and are typical of chaparral-dominated landscapes.

Normalized Difference Vegetation Index (NDVI)

In general, NDVI displayed significant differences in the WUI regions than in the non-WUI regions of the pre-wildfire study area models. On July 7, 2009, there was an abundance of vegetation. Spatially, WUI regions displayed positive and negative NDVI index values equivalent to healthy and unhealthy vegetation (figure 3). Northern WUI regions captured smaller plots of dispersed green vegetation. In contrast, Southwestern WUI regions and WUI regions near the bodies of water displayed a larger spatial arrangement of greener vegetation. Some of the WUI regions showed neutral NDVI values representing urbanized areas such as roads and houses.

Pre-wildfire non-WUI regions displayed mixed results based on the elevations. Non-WUI regions in higher elevations revealed unhealthier vegetation than in lower elevations. Based on the topography, land regime, and degree of fire intensity, the non-WUI regions were more vulnerable and combustible at higher elevations than at lower elevations. Higher elevations led to faster fire progression due to the heat rising in the air. The fire ignitions at high elevations demonstrated a distinct relationship between higher elevations and landscape. As a result, the pre-wildfire WUI regions had comparable spatial arrangements of green vegetation to the pre-wildfire non-WUI regions.

Post-wildfire, the NDVI values were overall neutral and represent dead vegetation (figure 3). WUI and non-WUI regions recorded similar spatial patterns of non-productive and unhealthy vegetation. Within the WUI, there were WUI defining characteristics such as houses and buildings.

Normalized Difference Burn Ratio (nDBR)

The nDBR of the Station Fire measured a change in biomass levels by calculating the difference between the pre-wildfire and the post-wildfire image. The Station Fire burn severity analyzed the regions of different burn severities post-wildfire. Figure 4 indicated WUI areas were primarily defined as low fire severity. Northern WUI regions displayed low fire severity and moderate fire severity. Similarly, Southwestern WUI regions consisted of unburned and low fire severity. Unburned nDBR negative values denoted insignificant changes in predicted vegetation regrowth. Low fire severity measured small, positive nDBR values, which predicted a slower vegetation regrowth period. Moderate fire severity quantified large, positive nDBR values, indicating the slowest vegetation regrowth period.

On the other hand, non-WUI areas displayed a range of nDBR values. The non-WUI areas generally consisted of unburned, low fire severity, and moderate fire severity in high and low elevations. The eastern non-WUI areas showcased a dominant unburned area. High elevations suggested moderate fire severity and low elevations suggested low fire severity. The non-WUI did not have a concrete rebound arrangement when compared to the WUI. Therefore, the vegetation regeneration pattern in the non-WUI varied differently than the WUI.

Figure 2

Digital Elevation Model (DEM) of the 2009 Station Fire showing elevation variation.

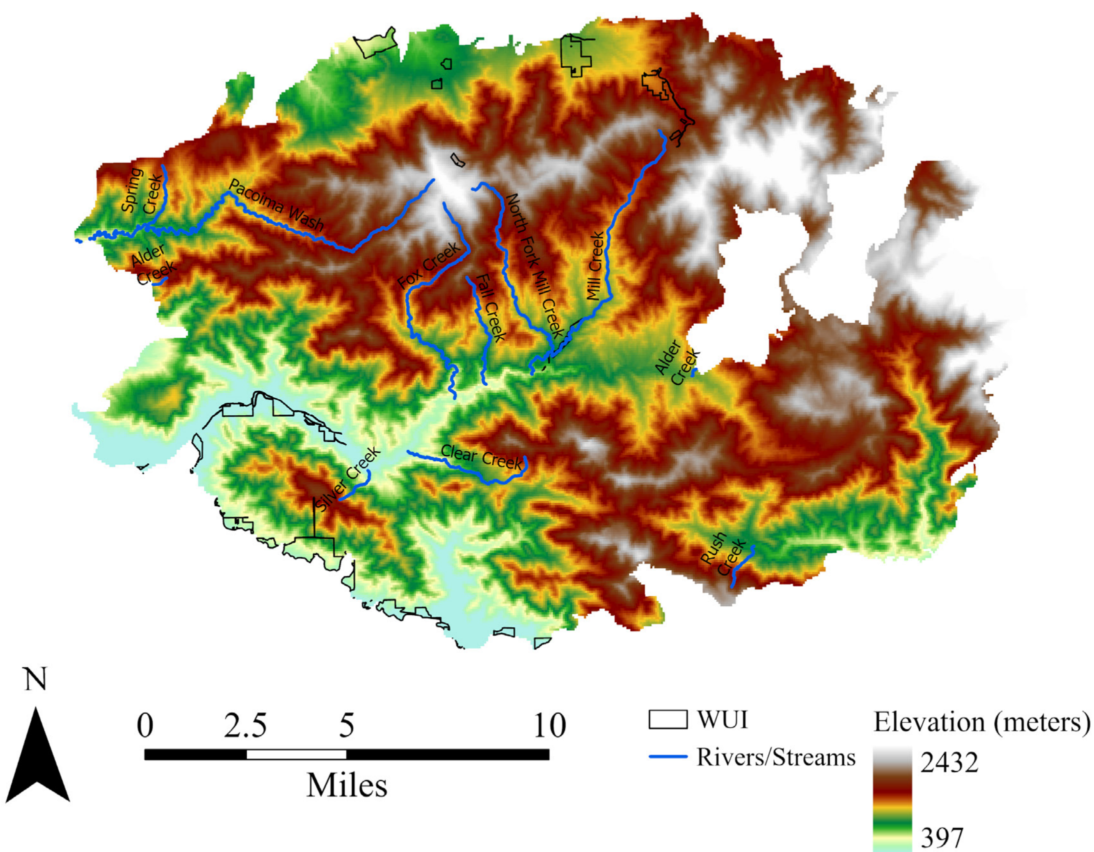


Figure 3

Pre-wildfire NDVI , July 7, 2009; Post-wildfire NDVI, October 25, 2009 of the Station Fire.

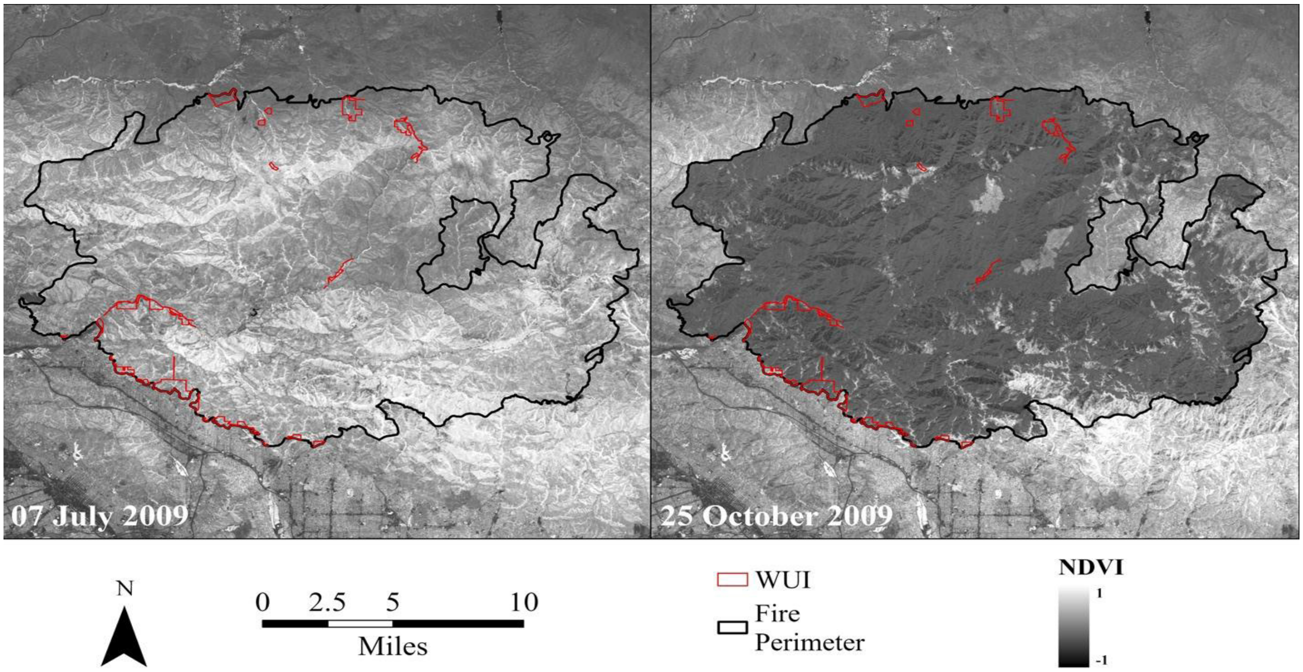
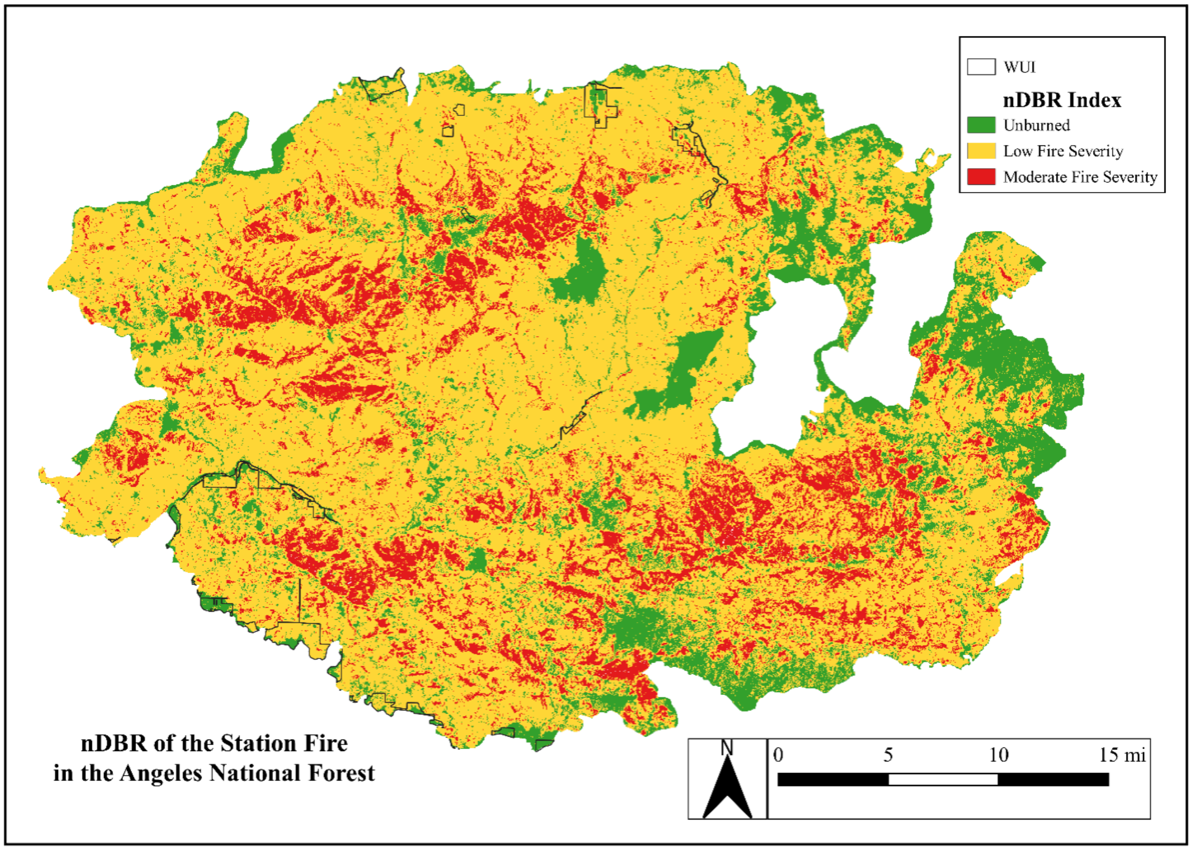


Figure 4

Normalized Difference Burn Ratio (nDBR) of the Station Fire. Unchanged, low fire severity, and moderate fire severity were listed to measure future regeneration.



LiDAR Above-Ground Biomass Analyses

There was no significant difference in 2009 above-ground biomass between WUI (M = 10,989.31, SD = 2,098.99) and non-WUI (M = 10,163.75, SD = 747.14) regions; t (38) = -1.66, p = 0.10. The 2016 analysis also did not show a significant difference in biomass between WUI (M = 19,9075.40, SD = 119,454.98) and non-WUI (M = 232,784.30, SD = 36,866.54) regions; t (38) = 1.21, p = 0.23 (figure 5).

Two simple linear regression models were conducted to compare vegetation recovery rates for WUI and non-WUI regions shown in figure 6. Simple linear regression models tested if non-WUI regions significantly predicted AGB. The overall regression was statistically significant ($R^2 = 0.95$, $F_{1,38} = 729$, $p < 0.01$). For WUI regions, too, there was a statistically significant regression ($R^2 = 0.57$, $F_{1,38} = 49.57$, $p < 0.01$).

The two-way ANOVA analysis showed a significant interaction between the type of region and fire severity (F1, 36 = 14.54, p <= 0.01) (figure 7). Simple main effects analysis showed that the type of region did not have a statistically significant effect on post-wildfire ABG regrowth (p = 0.13). Simple main effects analysis yielded a statistically significant impact on the level of fire severity and post-wildfire ABG regrowth (p = 0.01).

Discussion

The study hypothesized that aboveground biomass would recover differently post-wildfire based on the NDVI, nDBR, and the level of fire severity and the type of region. Visual accounts of NDVI suggested the consumption of the majority of the vegetation post-fire. There was uniformity of the vegetation biomass pre-fire and post-fire when comparing WUI and non-WUI regions. The similar spatial litter of biomass in both regions showed that the vegetation biomass was resilient to human disturbances and different levels of fire severities. Seven years after the Station Fire, the biomass regenerated quickly, demonstrating similar seed dormancy patterns. In the presence of humans, the overall vegetation thrived in fire-prone environments.

Visual accounts of nDBR predicted specifically that WUI regions would contain less abundant AGB than

Figure 5

The difference in 2009 and 2016 above-ground biomass for WUI and non-WUI regions. The figure on the left demonstrates the similar mean chaparral AGB for the WUI and non-WUI regions post-wildfire in 2009. The figure on the right demonstrates the similar mean chaparral AGB for the WUI and non-WUI regions seven years after the fire in 2016. There was an outlier for 2009 and 2016 post-wildfire and seven years after the fire.

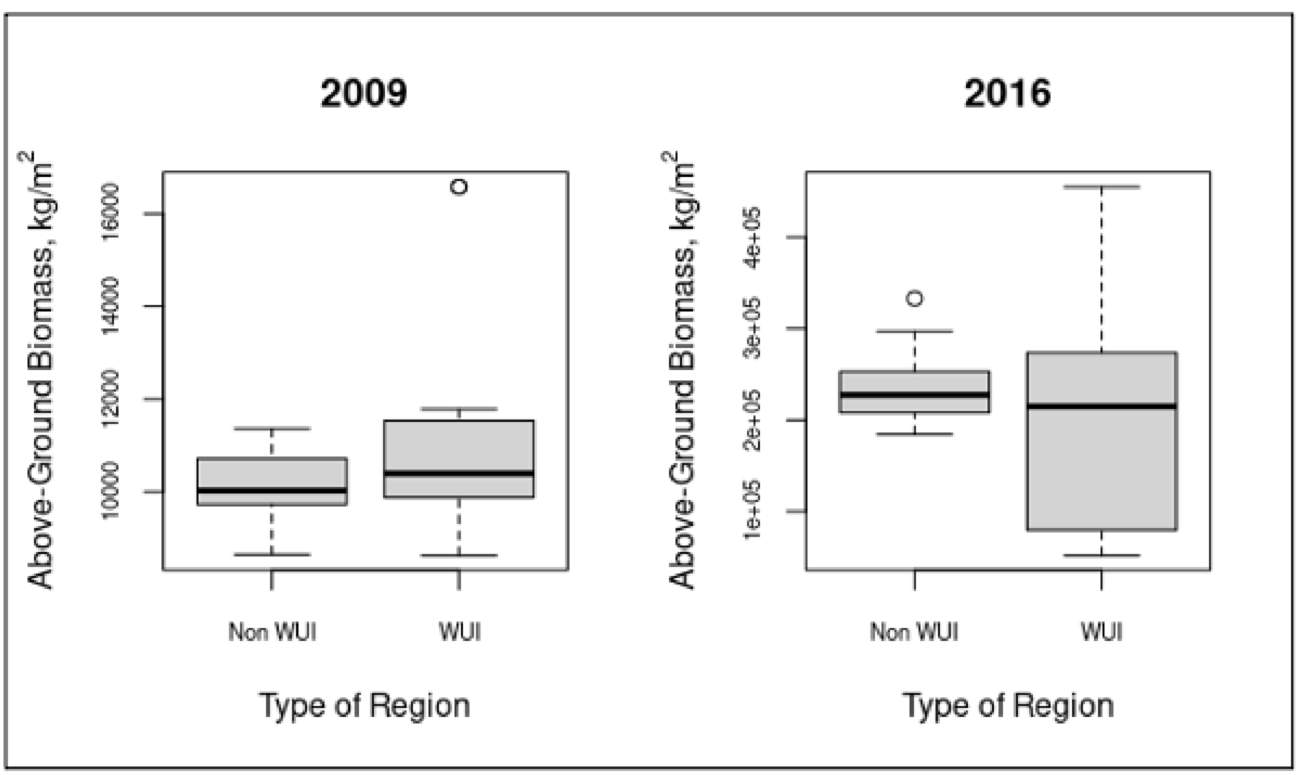


Figure 6

Vegetation recovery rates for WUI and non-WUI regions. The figures (from left to right) depict the individual plots acquired from 2009 and 2016 for the WUI and non-WUI regions, respectively. The blue line demonstrates the linear regression line and slope to quantify the chaparral AGB recovery from 2009 to 2016. Non-WUI regions exhibited a faster rebound slope than the WUI region.

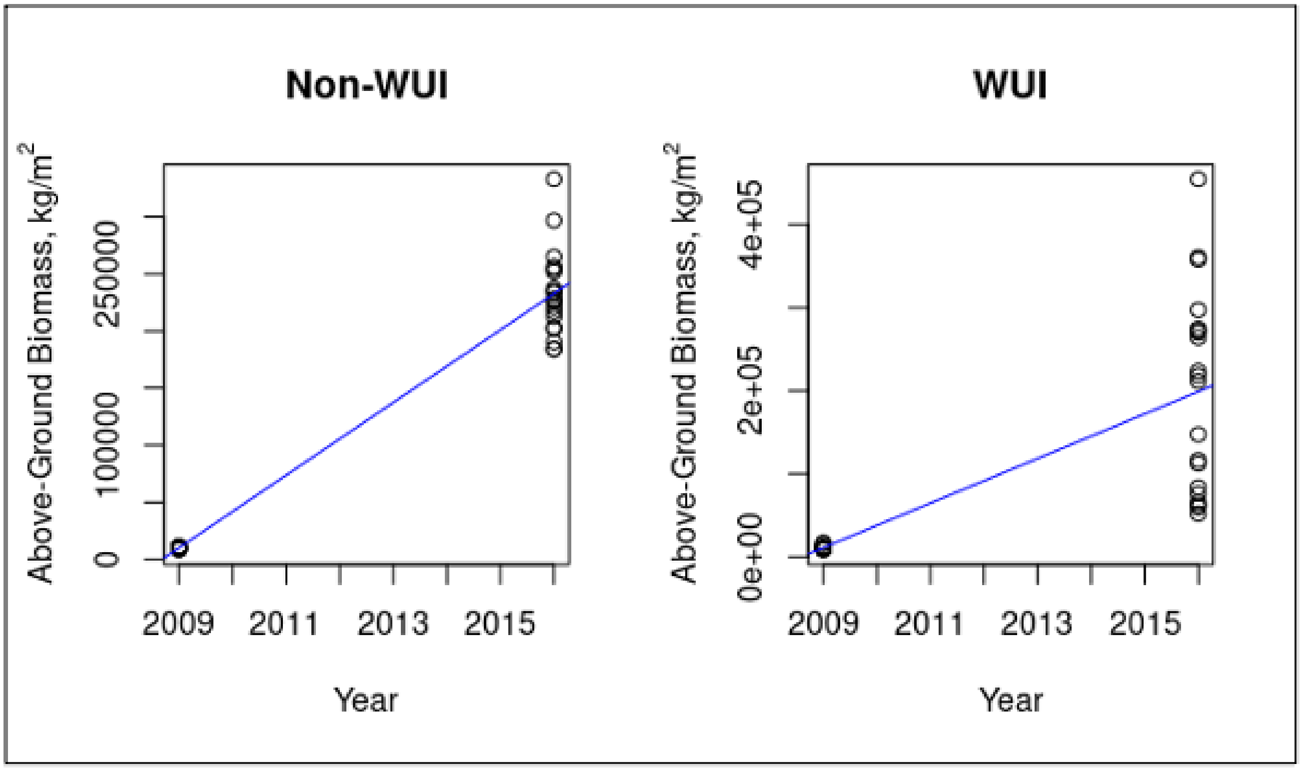
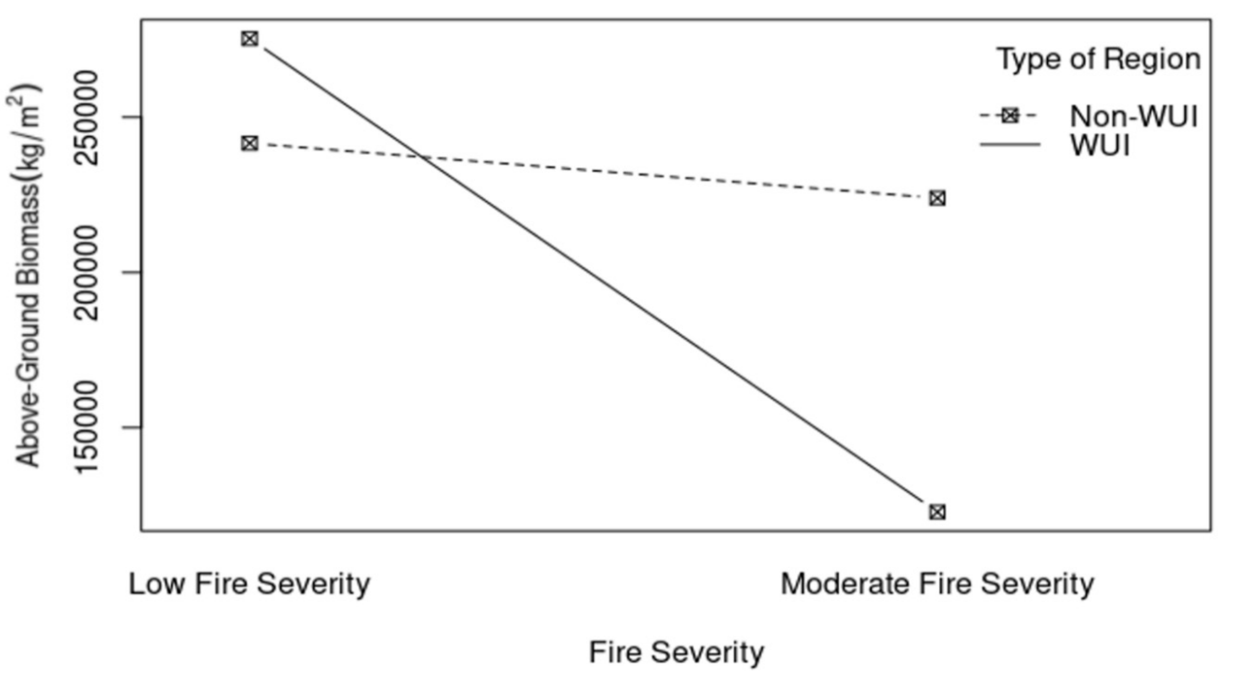


Figure 7

Interaction between the type of region and the type of fire severity level. The mean chaparral AGB for 2016 data was quantified by analyzing the severity and type of region of fire. This resulted in an interaction between the two independent variables. The mean chaparral AGB were similar for the type of region and the mean AGB for the level of fire severity were significantly different.



non-WUI regions due to heightened human activity. This hypothesis was not supported by the analyses, which meant that there were other contributing factors as to why vegetation biomass was abundant in both WUI and non-WUI regions. Elevation was one of the visual models that aligned with the original hypothesis. Though WUI regions were in lower elevations, the vegetation biomass was able to regenerate quicker than in higher elevations. In the lower elevations, there was low fire severity. The crown cover retained its structure and regrew faster than in rural areas. Because higher elevations consisted of moderate fire severity in the non-WUI region, the ecosystem was able to adapt and succeed in these fire prone environments quickly. Based on the linear regression analyses, the vegetation recovery period was comparable for WUI and non-WUI in 2009 through 2016. Although the rates of recovery were relatively similar, the vegetation biomass in the WUI was lower than in the non-WUI. This slight distinction should not be overlooked because it indicates that urbanization plays a minor role in vegetation recovery. The similarity was also attributed to how robust the chaparral ecosystem is ubiquitous to the environment. The vegetation structure of the chaparral post-fire was more easily converted into other vegetation types, usually non-native grassland, when it experienced several changes to its fire regime.

The mapping of aboveground biomass was based on fire severity and the type of region associated with higher fire risks in WUI than in non-WUI regions. Based on the given data, WUI expansion might have an influence in exacerbating the vulnerability of the regions to higher wildfire intensities and combustion. The level of fire severity depended on the type of region. It should be noted that overall, AGB did not elicit significant differences between WUI and non-WUI regions. The general classes (low fire severity and moderate fire severity) were associated with the region (non-WUI and WUI). Other factors such as temperature, microclimates, and precipitation may serve as reasons for an equal vegetation rebound in WUI and non-WUI regions.

Some limitations of the study were attributed to the Landsat 5 TM+ satellite images. With a temporal resolution of sixteen days, Landsat 5 TM+ monitored a small range of areas. A close temporal relationship between the satellite images before and after the fire was required for the NDVI and nDBR spectral indices. Errors in the data scanning process can occur due to the timeframe of the satellite images. In addition to the spatial resolution, there was another limitation to the study. Because Landsat 5 TM+ has a spatial resolution of 30 m, the pixelation of images did not capture detailed information. Higher resolution images will increase precision and accurately define vegetation biomass.

Another limitation of the study was the acquisition of the temporal data. Two years of data were analyzed in the study, but the results are not clearly indicative of fire recovery. There is a possibility that vegetation in the WUI could have recovered more quickly and then slowed down, resulting in a lower average biomass in the WUI. Data access limitations made it difficult to accurately depict recovery patterns.

A major concentration of chaparral vegetation was found in the Angeles National Forest following the Station Fire. It exhibited a range of phenotypic colors, from green to brown. Several types of chaparral vegetation can be identified by their differences in coloration. There is also the possibility that the WUIs contain non-native tree and shrub species cultivated for landscaping, and which are regularly watered, which might influence the NDVI of the WUIs and potentially affect the severity index. The NDVI could have underestimated healthy vegetation in the WUI regions. In contrast to NDVI, nDBR measures vegetation recovery based on fire severity. It is possible to misinterpret post-fire images as arid and dry areas due to drought instead of a wildfire.

Conclusion

Comparing vegetation biomass in the WUI and non-WUI regions post-wildfire of the Station Fire in the Angeles National Forest allows us to better understand vegetation regrowth in the presence of human disturbances. The land use and land cover type in rural areas also play a significant role in vegetation rebound. First, the vegetation biomass responded similarly in WUI and non-WUI regions in both 2009 and 2016. Second, the vegetation linear succession was analogous in WUI and non-WUI regions. Third, the level of fire severity yielded a significant effect on the post-fire biomass regrowth from 2009 to 2016. While this is the result of the uniqueness of the chaparral vegetation, it reflects how the chaparral can survive short-interval and long-interval fires in conjunction with human disturbances. The chaparral is well-adapted to recurring burning; however, the wildfire prevalence can create dissonance for the future based on higher fire severities. The study revealed new information about the correlation between high elevations and moderate levels of fire severity. Fires at higher elevations caused more destruction by damaging the vegetation composition and increasing the susceptibility to crown fires. As a result, the fire patterns at higher elevations removed the plant crown cover and reduced seed dormancy. It is also important to note that the chaparral community will thin with the repeated burning of these areas. Moderate severities that occur on slopes can increase the susceptibility to surface runoff, influence the repellency of the soil, and reduce the vegetation biomass in these elevations. Moderate fire severities are fatal for subsequent wildfires. Moderate fire severity and high elevations have the tendency to reburn post-wildfire. While it is possible for the chaparral to be well-adapted and resilient to any extreme climatic and anthropogenic factors, human disturbances may play a minimal role in vegetation rebound. To better understand the implications of these results, future research should consider examining water quality, slope, and aspect, to address the similarities of recovery rates in WUI and non-WUI regions. Carbon sequestration should also be assessed to measure plant productivity.

References

Barro, S. C., & Conard, S. G. (1991). Fire effects on California chaparral systems: an overview. *Environment International*, *17*(2), 135–149. https://doi.org/10.1016/0160-4120(91)90096-9

California Department of Forestry and Fire Protection's Fire and Resource Assessment Program (FRAP, 2021). Post-fire soil erosion. Retrieved September 15, 2021, from https://frap.fire.ca.gov/mapping/gis-data/

Efthimiou, N., Psomiadis, E., & Panagos, P. (2020). Fire severity and soil erosion susceptibility mapping using multi-temporal Earth Observation data: The case of Mati fatal wildfire in Eastern Attica, Greece. *CATENA*, 187, Article 104320. https://doi.org/10.1016/j.catena.2019.104320

Eidenshink, J., Schwind, B., Brewer, K., Zhu, Z.-L., Quayle, B., & Howard, S. (2007). A project for monitoring trends in burn severity. *Fire Ecology*, *3*(1), 3–21. https://doi.org/10.4996/fireecology.0301003

Gilbert, M. (2019). Wildland Urban Interface in CA. Retrieved September 15, 2021, from https://services1.arcgis.com/pf6KDbd8NVL1IUHa/arcgis/rest/services/Wildland_Urban_Interface_vector/FeatureServer

Guo, X., Coops, N. C., Tompalski, P., Nielsen, S. E., Bater, C. W., & John Stadt, J. (2017). Regional mapping of vegetation structure for biodiversity monitoring using airborne lidar data. *Ecological Informatics*, 38, 50–61. https://doi.org/10.1016/j.ecoinf.2017.01.005

Holtzclaw, J. (2021). California Fire Perimeters 1878–2020. Retrieved September 15, 2021, from https://services.arcgis.com/jIL9msH9OI208GCb/arcgis/rest/services/California_Fire_Perimeters_1878_2019/FeatureServer

Keeley, J. & Safford, H. (2016). THREE. Fire as an Ecosystem Process. In H. Mooney & E. Zavaleta (Ed.), *Ecosystems of California* (pp. 27-46). Berkeley: University of California Press. https://doi.org/10.1525/9780520962170-007

Levin, D. (2019). Vegetation recovery after wildfire in the Santa Monica mountains: A remote sensing analysis [Bachelor's thesis, University of Pennsylvania]. https://www.researchgate.net/publication/340874625_Vegetation_Recovery_After_Wildfire_in_the_Santa_Monica_Mountains_A_Remote_Sensing_Analysis

Martín-Alcón, S., Coll, L., De Cáceres, M., Guitart, L., Cabré, M., Just, A., & González Olabarría, J. R. (2015). Combining aerial LiDAR and multispectral imagery to assess postfire regeneration types in a Mediterranean forest. *Canadian Journal of Forest Research*, 45(7), 856–866. https://doi.org/10.1139/cjfr-2014-0430

McCarley, T. R., Kolden, C. A., Vaillant, N. M., Hudak, A. T., Smith, A. M., Wing, B. M., Kellogg, B. S., & Kreitler, J. (2017). Multi-temporal LiDAR and Landsat quantification of fire-induced changes to forest structure. *Remote Sensing of Environment,* 191, 419–432. https://doi.org/10.1016/j.rse.2016.12.022

Miller, J. D., & Thode, A. E. (2007). Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR). *Remote Sensing of Environment*, *109*(1), 66–80. https://doi.org/10.1016/j.rse.2006.12.006

National hydrography (n.d.). National Hydrography Dataset. Retrieved November 7, 2021, from https://www.usgs.gov/core-science-systems/ngp/national-hydrography/national-hydrography-dataset?qt-science_support_page_related_con=0#qt-science_support_page_related_con.

Peterman, W. (2013). 90 m DEM of California, USA. Retrieved October 20, 2021, from http://databasin.org/datasets/78ac54fabd594db5a39f6629514752c0

Rull, V., González-Sampériz, P., Corella, J.P., Morellón, M., & Giralt, S. (2011). Vegetation changes in the southern Pyrenean flank during the last millennium in relation to climate and human activities: the Montcortès lacustrine record. *Journal of Paleolimnology*, 46(3), 387–404. https://doi.org/10.1007/s10933-010-9444-2

Schrader-Patton, C. C., & Underwood, E. C. (2021). New Biomass Estimates for Chaparral-Dominated Southern California Landscapes. *Remote Sensing (Basel, Switzerland*), 13(8), 1581–. https://doi.org/10.3390/rs13081581

Storey, E. A., Stow, D. A., O'Leary, J. F., Davis, F. W., & Roberts, D. A. (2021). Does short-interval fire inhibit postfire recovery of chaparral across southern California? *The Science of the Total Environment*, *751*, 142271–142271. https://doi.org/10.1016/j.scitotenv.2020.142271

Syphard, A. D., Rustigian-Romsos, H., & Keeley, J. (2021). Multiple-scale relationships between vegetation, the wildland–urban interface, and structure loss to wildfire in California. Fire, 4(1), 12. https://doi.org/10.3390/fire4010012

Tepley, A. J., Thomann, E., Veblen, T. T., Perry, G. L. W., Holz, A., Paritsis, J., Kitzberger, T., & Anderson-Teixeira, K. J. (2018). Influences of fire-vegetation feedbacks and post-fire recovery rates on forest landscape vulnerability to altered fire regimes. *Journal of Ecology*, 106(5), 1925–1940. https://doi.org/10.1111/1365-2745.12950

Thompson, R., Kaplan, C., Gomberg, D. (2021). The Station Fire: An example of a large wildfire in the absence of significant winds. Retrieved October 20, 2021, from https://www.weather.gov/media/wrh/online_publications/talite/talite1002-1.pdf

Wulder, M., White, J., Alvarez, F., Han, T., Rogan, J., & Hawkes, B. (2009). Characterizing boreal forest wildfire with multi-temporal Landsat and LIDAR data. *Remote Sensing of Environment*, 113(7), 1540–1555. https://doi.org/10.1016/j.rse.2009.03.004