Drought Disturbance Impacts on Sierra Nevada Ecosystems: A Remote Sensing Approach

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ABSTRACT

The western region of North America has been characterized by a recurrent and profound phenomenon of drought, with certain episodes spanning over decades. An instance of such severe droughts was witnessed in California from 2013 to 2016, which represents the most intense recorded dry spell in the state's history. The increasing frequency and intensity of droughts, compounded by additional disturbances, pose a threat to ecosystem integrity and present challenges to managing these areas for ecosystem services and multiple-use objectives. I found that using Landsat 8 satellite imagery, coupled with remote sensing technology and indices has proven to be a promising method for monitoring these drought disturbances. Results showed that the normalized difference vegetation index (NDVI) and the enhanced vegetation index (EVI) are strong indices for detecting vegetation loss due to drought, while the normalized difference water index (NDWI) performed well in identifying drought in areas with water covers. The study suggests that combining NDWI with a vegetation index like NDVI or EVI can provide a more comprehensive understanding of drought impacts. The effectiveness of these indices varies depending on ecosystem conditions, and EVI was particularly effective in monitoring the 2013-2016 drought in California. By utilizing these indices in tandem, it is possible to detect changes in ecosystem conditions, generate useful data for developing drought preparedness plans, pinpoint the optimal timing for water conservation initiatives, and facilitate the management of responses in land use.

KEYWORDS

California Drought, Landsat 8, Normalized Difference Water Index (NDWI), Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Ecosystem Integrity

INTRODUCTION

Drought is a fundamental feature of the climate of western North America. Over the last century, regions of the western United States have experienced protracted decadal-scale dry periods (Griffin and Anchukaitis 2014). Recently, California has experienced some of the worst conditions it has seen since droughts started to be recorded. Droughts are occurring more frequently and increasing in severity; the 2012–2016 California drought was the most severe drought to hit California in the past 1200 years (Griffin and Anchukaitis 2014). This means that both residents and policymakers need to understand the full severity of this specific natural disturbance and track some of the predicted and already observed long term impacts. Ecological disturbances largely involve concepts that not only speak to environmental concerns but also work within the realm of human communities (Sivils 2006). Since almost all residents are now feeling the effects of drought, we need to understand the full severity of this specific natural disturbance, starting with identifying areas of significant damage and where some of the roots of these impacts are coming from. Influential ecosystems have been displaced or destroyed, with a remarkable amount of impactful species disappearing and governing watersheds emptied.

The increase in compounding disturbances, such as hotter droughts coupled with insect outbreaks, has significant impacts on the integrity of forested ecosystems and their subsequent management for important ecosystem services and multiple-use objectives (Pile et al. 2019). The decrease in health of forested ecosystems has direct, noticeable impacts on the health of nearby communities and cities. Forests play a critical role in maintaining the balance of the water cycle, but this system can diverge from an equilibrium state when either natural or anthropogenic disturbances occur (Antonarakis 2018). At high elevations, increased temperatures elevate freezing lines, intensify albedo feedbacks, and reduce snowfall, all of which accelerate seasonal flows of snowmelt driven streams (Berg and Hall 2017). The Sierra Nevada snowpack is a critical natural reservoir for the greater Bay Area and Sierra foothills, which means if the water cycle in the Sierras is damaged or depleted then this means less water availability for local ecological communities. Due to the loss of immense amounts of forest, this has consequently impacted large watershed systems, meaning many plant and animal species are displaced. It is predicted that natural disturbances do not remove species preferentially and that species replacement is initiated by catastrophic events (Platt and Connell 2003). This indicates that species should be randomly displaced from these communities, but the problem reveals that crucial amounts of vegetation have died off due to the decline in overall water availability from the drought disturbance.

Natural factors affecting forest disturbances are among the most significant drivers transforming the earth. Due to this reason remote sensing technologies are widely used for forest cover monitoring under climate change and human impact (Polevshchikova 2019). Spatially explicit forest disturbance maps coupled with extrapolation models predicted mortality and severe structural damage to ~320 million large trees in US forests (Chambers et al. 2007). Large scale studies that assess patterns of disturbance over areas that are isolated from humans or ground service observations require remote sensing and aerial analysis. Object-based image analysis can be more useful when analyzing high resolution imagery (Blaschke et al. 2014). Using remote sensing techniques will be an advantageous strategy for assessing the effects of drought conditions, not only for convenience but also for specificity. Identifying patterns of consequential vegetation loss will be crucial when comparing with the scale of water availability in the specific study site, helping predict future impacts and provide feedback for preventative measures rather than response actions.

By using remote sensing and GIS technology, it is possible to track the disturbance of the recent 2013-2016 drought in Mariposa County of the Sierra Nevadas. In this study I ask how has drought disturbance affected the overall ecosystem of Mariposa County within the Sierra Nevadas? I will be able to answer this broad analysis by breaking it down into three smaller scale questions. Starting with, how has estimated water availability changed in Sierra Nevadas since the drought disturbance by using NDWI? I predict that with higher temperatures and less precipitation, this leads to reduced snowpack and overall water availability for both water transpired into plants as well as within rivers and lakes. The second question that I ask is, how has vegetation density and greenness been affected by the drought by using NDVI? I anticipate to see that there will be overall less vegetation density due to limited water resources relating to the first question, but it will be engaging to see the difference between vegetation change detected by NDVI and NDWI. The last question I will ask is, how has vegetation density and greenness post drought disturbance by using EVI? I expect to see similar results to NDVI, as these are both vegetation indices, however, EVI is more sensitive in high density vegetation cover and has the potential to detect more loss. These questions require remotely sensed data such as satellite imagery in addition to geospatial data sets in order to calculate and visualize water index measurements as well as change in vegetation density.

METHODS

Study Site

I investigated Mariposa County, which is located directly between the northern and southern sections of the Sierra Nevada Mountain Range (37.47160 °N, 119.81492 °W). The two largest cities that reside within my study plot are Mariposa and Midpines which are located in the foothills of Yosemite Valley. Common ecosystem types within this area include Sierran Mixed Conifer Forests, Northern Mixed Chaparral, Mixed Montane Chaparral, and the more rare Valley Grassland (USGS 2022). The landscape terrain of this region consists of deep canyons, rivers, and rising mountains, containing three major hydrologic basins on the western side of the Sierra Nevadas (USGS 2022). These basins include the Merced River, Fresno River, and Lower Mariposa group of streams. The western side of this site has rolling hills that gradually increase to mountains when moving east, the elevation starts at around 2,000 feet and goes all the way up to around 6,000 feet, cutting off just before the Yosemite giant El Capitan. Temperatures within this location range from freezing to over 100 degrees fahrenheit depending on the topography, with precipitation also ranging from 15 inches in the west to 50 inches in the mountainous regions, however, this differs significantly when in drought conditions (MariposaCounty 2023). The study site is a fire adapted community where wildfire has been a major physical factor in the development of vegetation types and the overall ecosystem (USFS 2021).

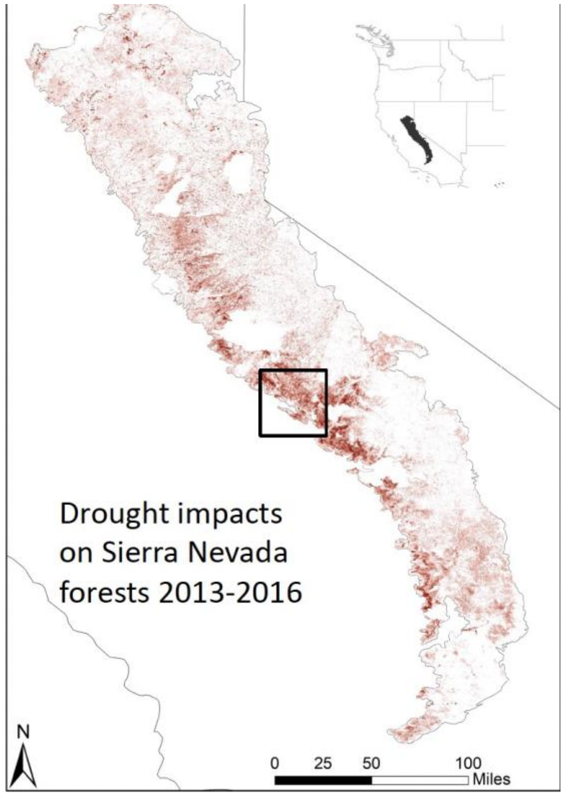


Figure 1. Source: Author 2022

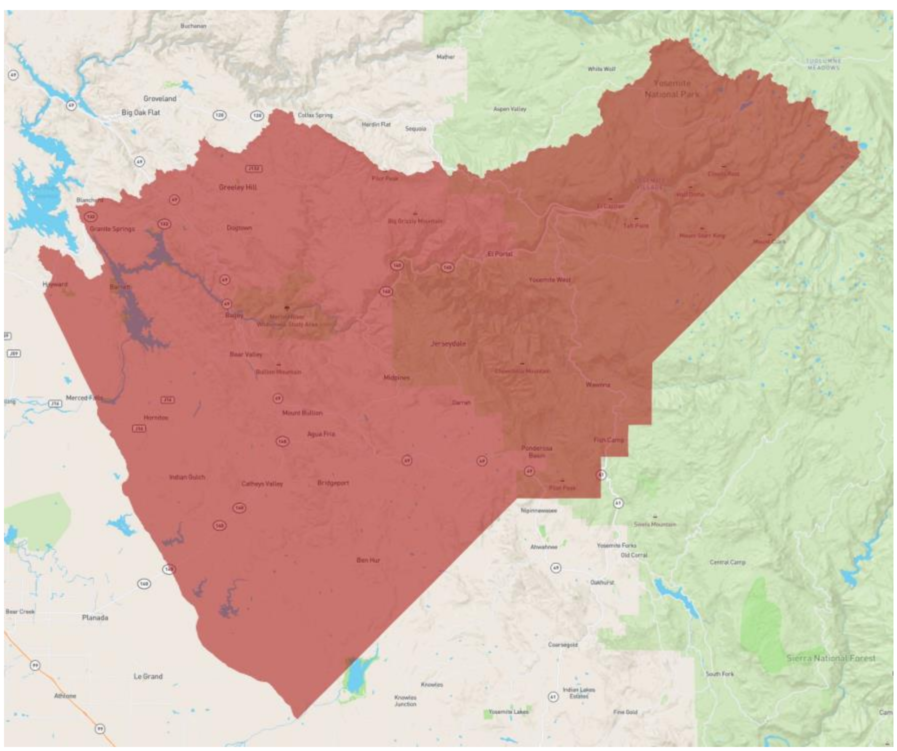


Figure 2. Map of Mariposa County. (MariposaCounty 2023)

NDWI Data Collection and Analysis

In order to answer how water availability has changed in the Sierra Nevadas since the drought disturbance, I accessed Landsat 8 imagery to run satellite image analysis. I chose to import USGS Landsat 8 Collection 2 Tier 1 and Surface Reflectance as my base image to run my analysis within Google Earth Engine. By using Collection 2 rather than Collection 1, improved the absolute geolocation, as well as cloud-optimized GeoTIFF format and globally available Level-2 surface reflectance and surface temperature products (Wulder et al. 2019). I used two remote sensing derived indices related to liquid water to analyze the water index and availability within the Sierra Nevada ecosystem. The normalized difference water index (NDWI), is proposed for remote sensing of vegetation liquid water from space. NDWI is a measure of liquid water molecules in vegetation canopies that interact with the incoming solar radiation. It is less sensitive to atmospheric scattering effects than NDVI (Gao 1996).

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

Equation 1. The first index related to liquid water that measures the change in water content of leaves using near-infrared and short-wave infrared bands.

Once I imported the Landsat data, I set filter dates for the image collection from July 1, 2013 to August 31, 2013, in order to avoid cloud coverage. I clipped the larger Landsat tile to fit into the perimeter of Mariposa County so that the calculated index did not use data from other areas. From here I used Equation 1 to calculate the NDWI for 2013 and added this layer to the map. I repeated the same process, using identical dates and areas to calculate NDWI for 2016. With access to both the 2013 and 2016 NDWI maps, I subtracted the 2013 values from the 2016 values and was able to find the ΔNDWI. I portrayed the ΔNDWI with a map that has a legend showing areas of both loss and growth, and their severity, over the entirety of the drought. I then produced two histograms within Google Earth Engine showing the NDWI values for 2013 and 2016, in order to help visualize the shift in the values from the start of the drought to the end.

Next, I used NDWI's second index related to liquid water that measures the water content within bodies of water. NDWI is a method that has been developed to delineate open water features and enhance their presence in remotely-sensed digital imagery. The NDWI makes use of reflected near-infrared radiation and visible green light to enhance the presence of such features while eliminating the presence of soil and terrestrial vegetation features (McFeeters 1996).

$$\mathrm{NDWI} = \frac{\mathrm{Green} - \mathrm{NIR}}{\mathrm{Green} + \mathrm{NIR}}$$

Equation 2. The second index for NDWI that measures the change in water content within bodies of water using green and near-infrared bands

This process used the same exact methods as the first NDWI index, except I plugged in Equation 2. The ΔNDWI map was still produced with a legend showing severity of loss and gain. This allowed me to see the change in water content among the various bodies of water without getting distracted by soil and terrestrial vegetation features. Both histograms were also produced showing the shift in NDWI values, still on the -1 to 1 scale, with the values showing differences from the first index.

NDVI Data Collection and Analysis

In order to answer how vegetation density and greenness has been affected by the drought, I accessed the same USGS Landsat 8 Collection 2 Tier 1 and Surface Reflectance imagery to run satellite imagery analysis through Google Earth Engine. Instead of using NDWI, I used normalized difference vegetation index (NDVI) as my metric to track the change in vegetation density across the 4 year drought. Vegetation indices, produced on 16-day intervals and at multiple spatial resolutions, provide consistent spatial and temporal comparisons of vegetation canopy greenness, a composite property of leaf area, chlorophyll and canopy structure (MODIS Web).

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

Equation 3. NDVI index that measures the change in vegetation greenness, density, and health using red and near-infrared bands.

I imported the Landsat data once again and set filter dates for the image collection from July 1, 2013 to August 31, 2013, to avoid cloud coverage. I clipped the larger Landsat tile to fit into the perimeter of Mariposa County and used Equation 3 to calculate the NDVI for 2013 and added this layer to the map. I repeated the same process, using identical dates and areas to calculate NDVI for 2016. With access to both the 2013 and 2016 NDVI maps, I subtracted the 2013 values from the 2016 values and was able to find the ΔNDVI. I portrayed the ΔNDVI with a map and legend showing severity of both loss and growth over the entirety of the drought. I produced two histograms within Google Earth Engine showing the NDVI values for 2013 and 2016, in order to help visualize the shift in the values from the start of the drought to the end.

Since NDVI is a vegetation index, I used LandTrendr's Pixel Time Series program within Google Earth Engine to track individual pixels impacted by drought from the Landsat Collection. LandTrendr takes a single point-of-view from a pixel's spectral history, like a band or an index, and goes through a process to identify breakpoints separating periods of durable change or stability in spectral trajectory, and records the year that changes occurred. These breakpoints, defined by year and spectral index value, allow us to represent the spectral history of a pixel as a series of vertices bounding line segments (LandTrendr 2023). I defined the year range to be from 2010 to 2020 so that I could see trends before and after the drought and used the same July and August dates as before. I selected NDVI as the index to analyze and chose a specific latitude and longitude of an area known to have been drought affected. This produced a time series map which allowed me to look at the index value of the location over ten years and identify when the changes occurred.

EVI Data Collection and Analysis

I used Google Earth Engine to access the same USGS Landsat 8 Collection 2 Tier 1 and Surface Reflectance satellite imagery of Mariposa County to look at vegetation change. This time I utilized the enhanced vegetation index (EVI) rather than NDVI to look at the change in vegetation greenness within dense areas of foliage. The EVI was developed to optimize the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring through a decoupling of the canopy background signal and a reduction in atmosphere influences (Huete et al. 2002).

$$\mathbf{EVI = G * ((NIR - R) / (NIR + C1 * R - C2 * B + L))}$$

Equation 4. EVI index that quantifies vegetation greenness using NIR, Red, and Blue bands. For Landsat 8, G = 2.5, C_1 = 6, C_2 = 7.5, and L = 1.

After importing the Landsat imagery, setting the summer filter dates, and clipping the image to Mariposa County, as completed in the previous sections, I used Equation 4 to produce 2013 and 2016 EVI maps. I looked at the difference between the two images by subtracting the 2013 EVI from the 2016 EVI, which showed the ΔEVI for green vegetation, producing a corresponding map and legend. I created the two histograms for 2013 and 2016 as well, helping visualize the somewhat dramatic shift in EVI values across the drought.

EVI is also a vegetation index, allowing me to use LandTrendr to track pixels over time. I filtered the years to range from 2010 to 2020 and used the same July and August dates as before. I selected EVI as the index and chose the identical latitude and longitude as the NDVI to analyze and compare results. This produced a time series map which allowed me to look at the index value of the location over ten years and identify when the changes occurred.

RESULTS

NDWI

Water Content Within Vegetation

The NDWI showed a large amount of water availability loss within vegetation structures, paired with a decent amount of gain over the entire landscape (Figure 3). On average, the county as a whole experienced little to no change, as illustrated by the large gray portions of land cover (Figure 3). NDWI values are similar to NDVI in that they are on a scale of -1 to 1, with -1 to 0 meaning bright surfaces with no vegetation or water content, and 0 to 1 having water content

(Gao 1996). When combining the near equal loss to gain ratio with the average minimal change of the environment, we see mean NDWI values of 0.08731 for 2013 and 0.07420 for 2016 (Figure 4). These mean values are centered around zero and show no significant difference, however the 2016 average is still lower than 2013, indicating some loss.

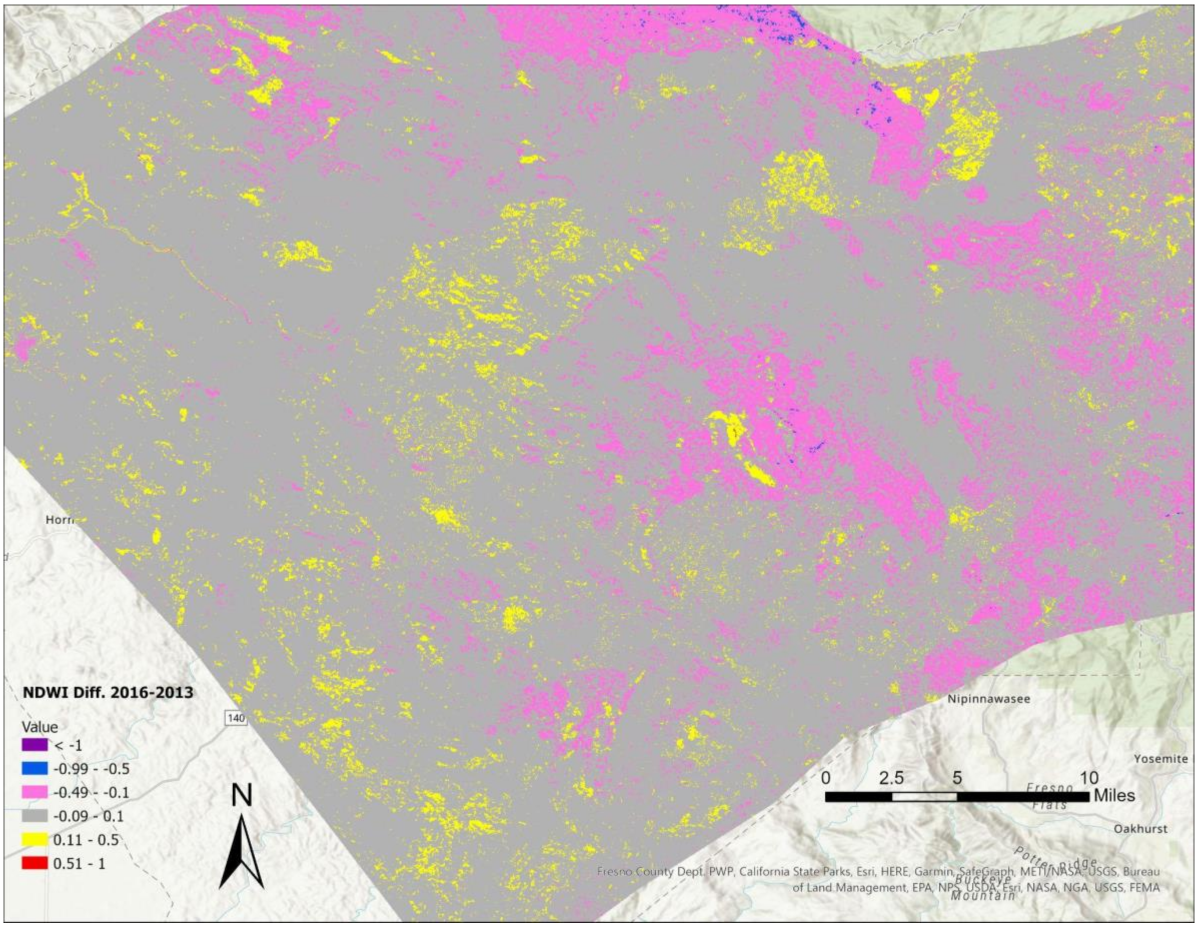
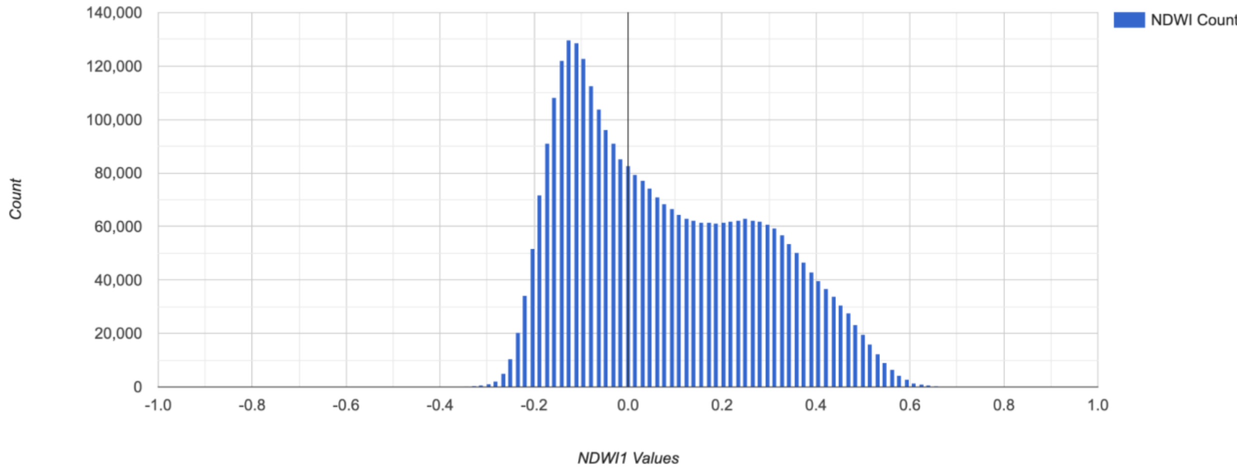


Figure 3. Map of ΔNDWI for water content within vegetation. Source: Author 2023

(A)



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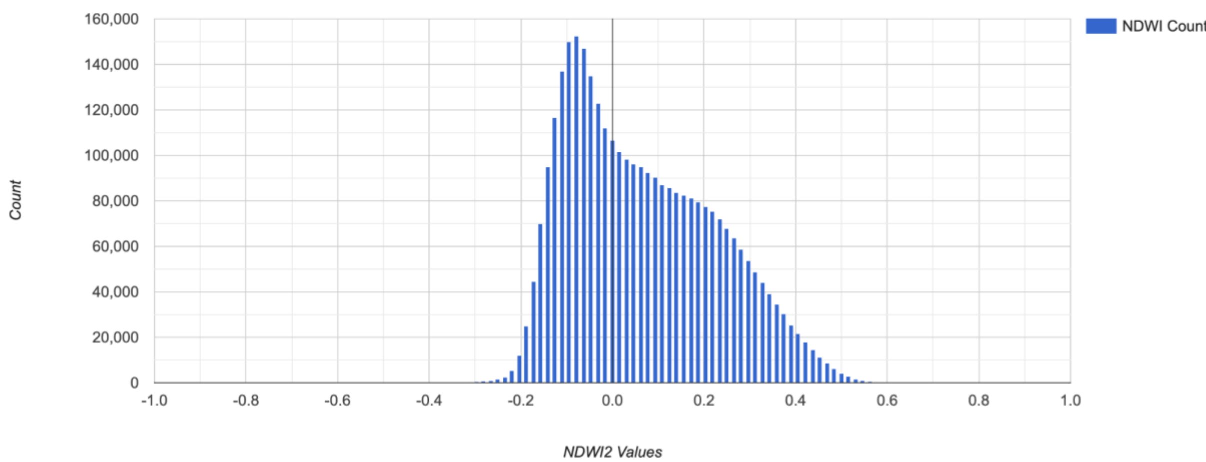


Figure 4. A: NDWI values for water content within vegetation in 2013, with a mean value of 0.08731 and standard deviation of 0.20317. B: NDWI values for water content within vegetation in 2016, with a mean value of 0.07420 and standard deviation of 0.16191. Source: Author 2023

Water Content Within Bodies of Water

I found that there was change in the water content within open water features in Mariposa County, where the large bodies of water, along with their tributaries, showed an overall decrease in available water (Figure 5). However, the index still identified regions of loss and gain in areas that are not open water features, leading to the map and histograms showing data that is not solely represented by lakes and rivers (Figures 5 and 6). A general rule of thumb for interpreting the NDWI values of open water features is that 0.2 to 1 represents water surface, -0.3 to 0.2

represents moderate drought and some aqueous surfaces, and -1 to -0.3 represents drought and non-aqueous surfaces (McFeeters 1996). I found that there are around 10,000 pixels between the values of 0.4 and 0.7 for 2013, which portrays the small amount of open water, while the average total NDWI value is -0.60843 meaning large areas of drought and non-aqueous surfaces (Figure 6). In 2016 the 10,000 open water pixels shifted to values at or below 0.4, signaling a loss in water content, illustrated by the pink areas in Figure 5. Whereas the total 2016 NDVI value mean is -0.58137, indicating a slight influx of water content (Figure 6).

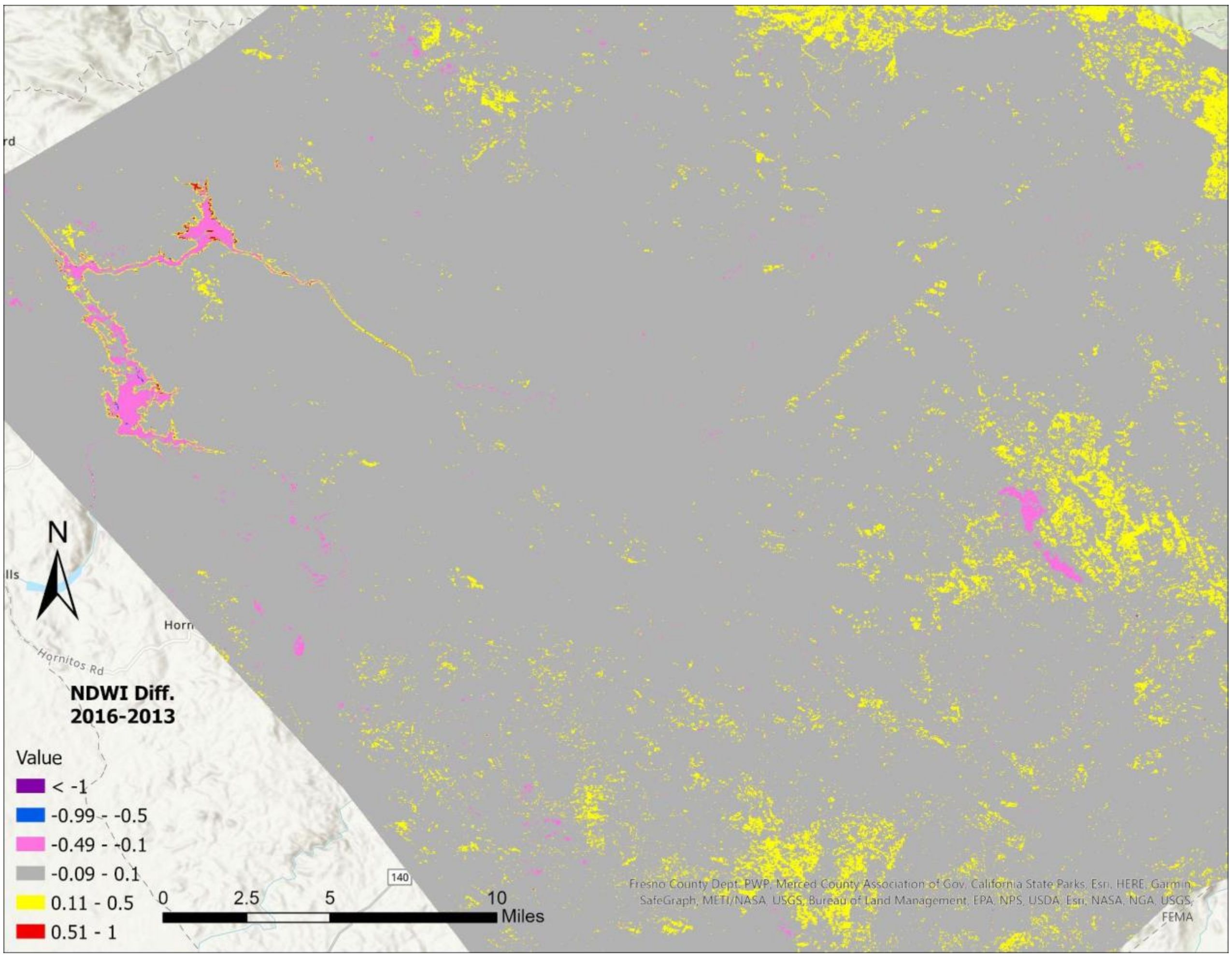
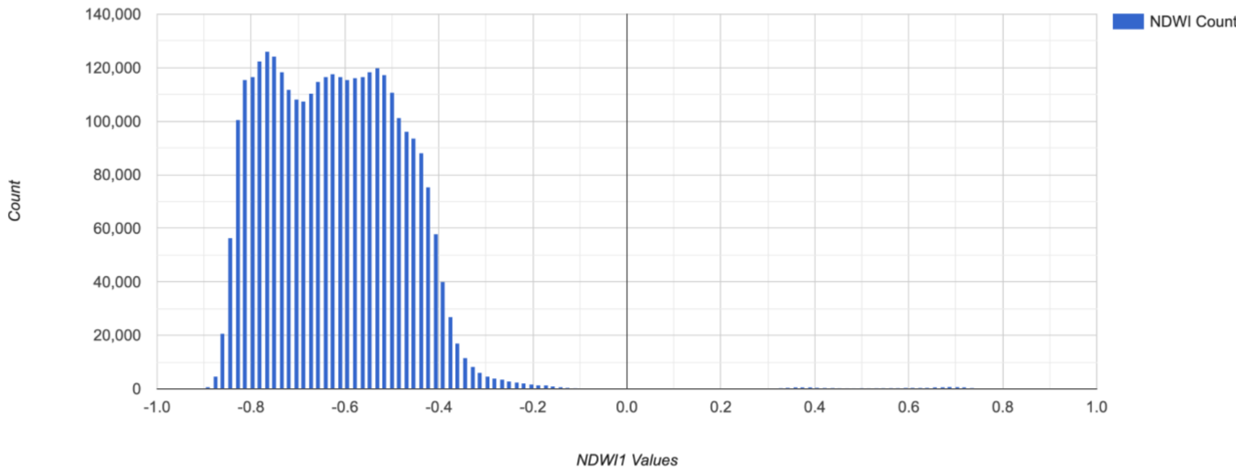


Figure 5. Map of ΔNDWI for water content within open water features. Source: Author 2023

(A)



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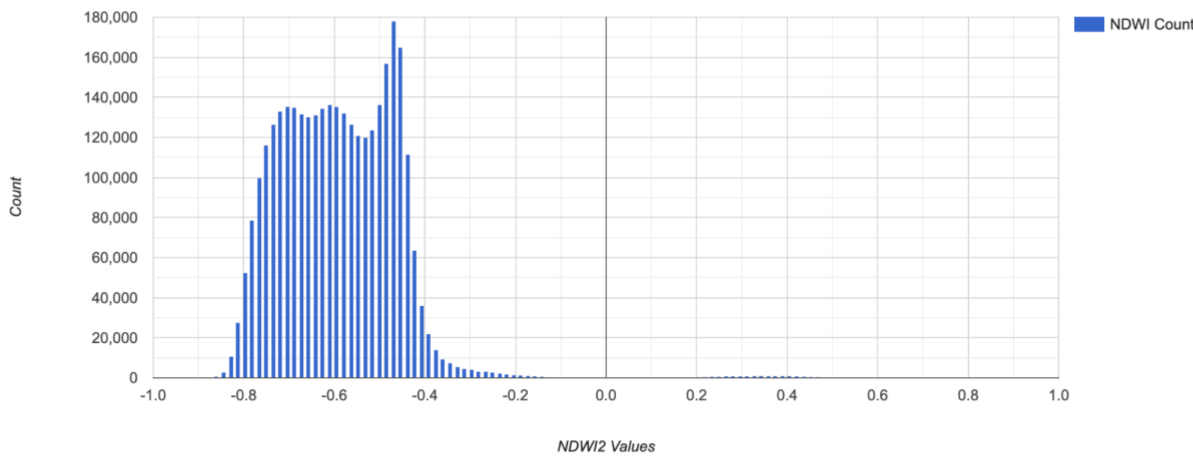


Figure 6. A: NDWI values for water content within open water features in 2013, with a mean value of -0.60843 and standard deviation of 0.15555. B: NDWI values for water content within open water features in 2016, with a mean value of -0.58137 and standard deviation of 0.13468. Source: Author 2023

NDVI

I found that the majority of the landscape within Mariposa County had insignificant change, although large areas of the environment did experience an immense amount of loss of green vegetation (Figure 7). There are still some small pockets of growth, however, these areas are mostly clumped around bodies of water. NDVI has a scale of -1 to 1, with negative values corresponding to barren areas such as sand and water, 0.2 to 0.4 values representing grassland and shrubs, and 0.5+ values corresponding to dense vegetation such as forests (USGS 2019). Even though we see extensive loss of green vegetation in Figure 7, the mean NDVI values for 2013 were 0.54733 and 0.50771 for 2016 (Figure 8). This does not show a significant decrease in NDVI from the beginning of the drought to the end, however, there was still a 0.03962 average loss of NDVI suggesting overall decline in vegetation greenness.

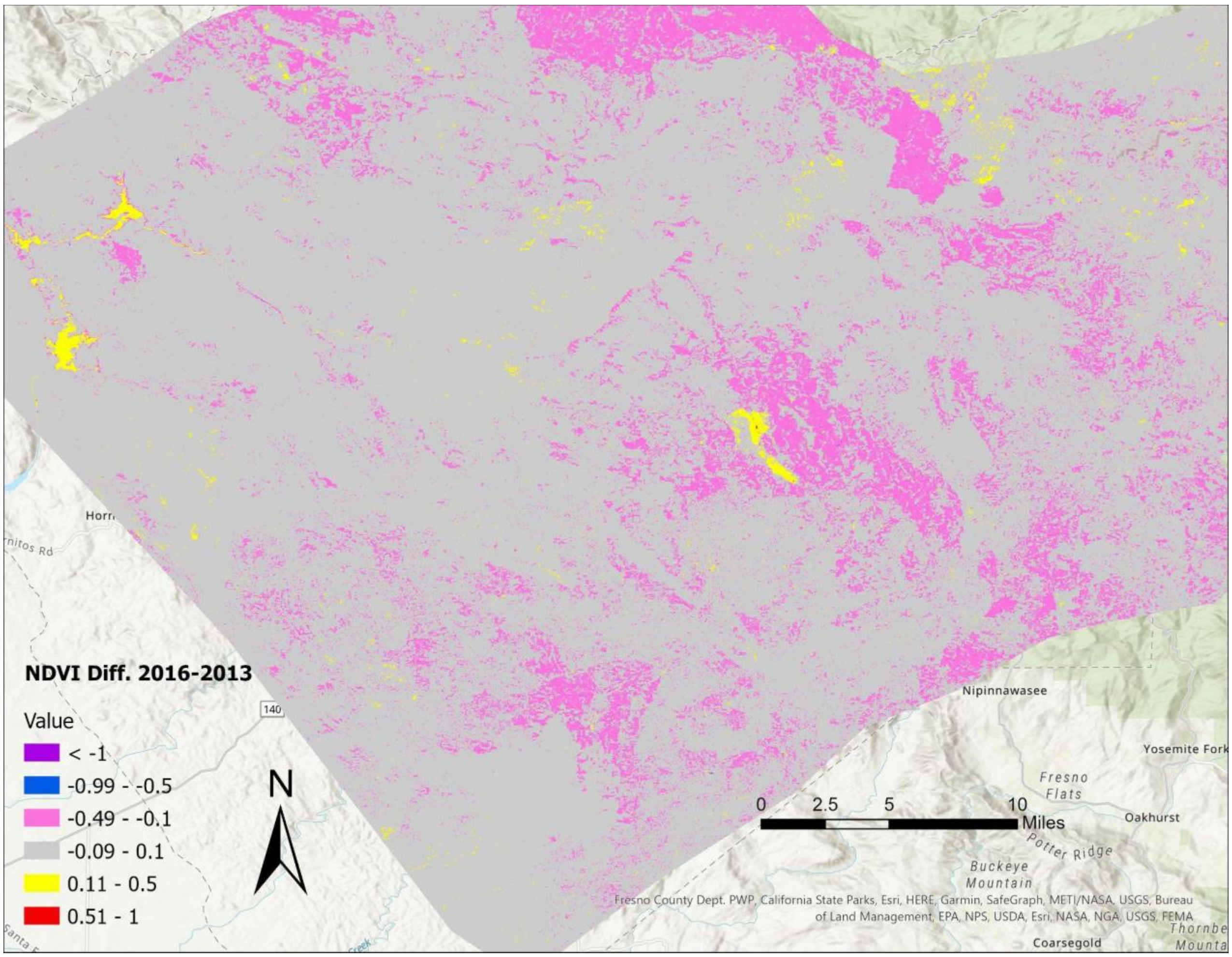
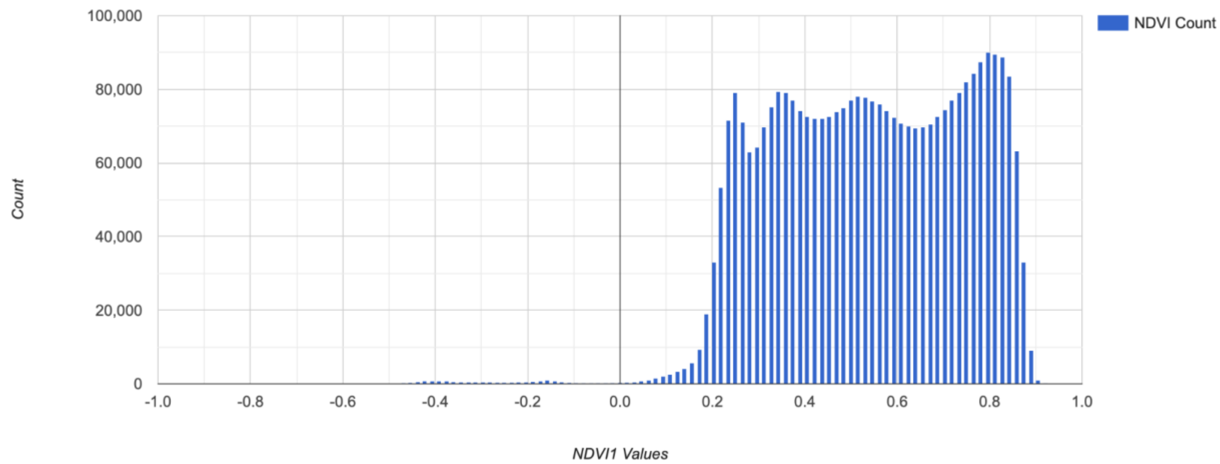


Figure 7. Map of ΔNDVI. Source: Author 2023

(A)



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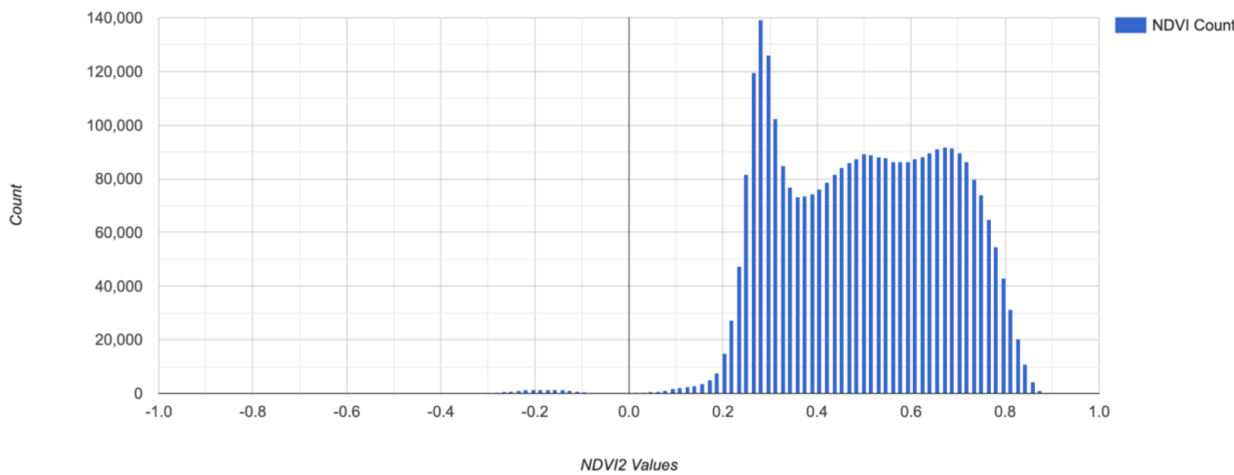


Figure 8. A: NDVI values for 2013, with a mean value of 0.54733 and standard deviation of 0.20582. B: NDVI values for 2016, with a mean value of 0.50771 and standard deviation of 0.17958. Source: Author 2023

After running LandTrendr, I found that this specific pixel experienced the drought disturbance starting directly in 2013 (Figure 9). The disturbance lasted roughly a year and had a magnitude or loss of about 0.25 on the NDVI scale. After 2014, the area began to recover and gained about 0.18 of the vegetation back until 2016 when the area plateaued and became stable again, only slightly lower than the pre drought values (Figure 9).

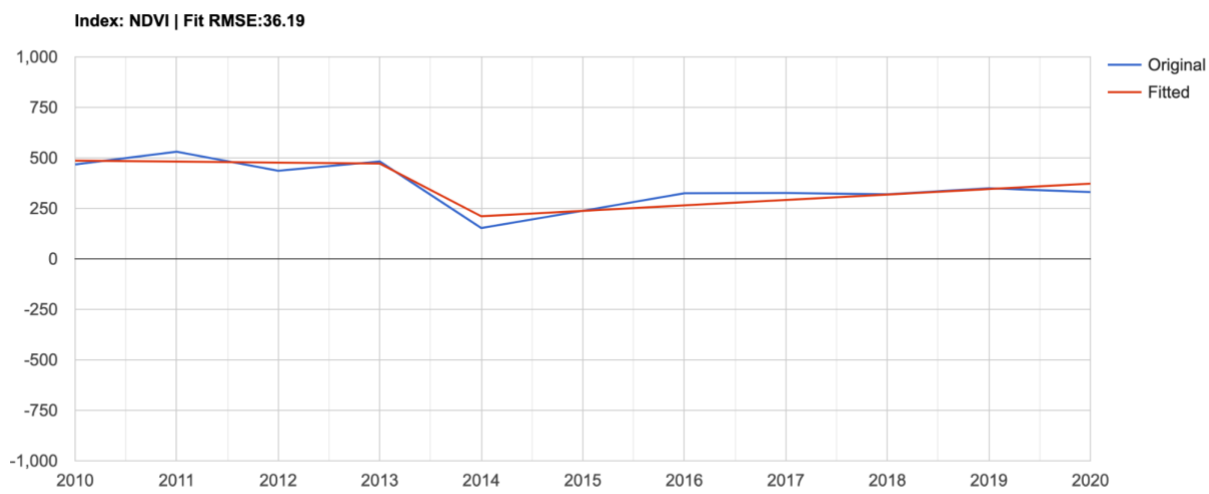


Figure 9. NDVI LandTrendr Pixel Time Series analysis of drought affected pixel (same pixel as EVI's LandTrendr). Source: Author 2023

EVI

I observed that the EVI results were very similar to the NDVI results, as they are both vegetation indices (Figures 7 and 10). EVI showed that there were also insignificant changes to most of the terrain, but a decent amount of areas experienced major loss (Figure 10). The regions that showed growth were also centered around bodies of water (Figure 10). EVI was the only index that I used not on the -1 to 1 scale, however, negative values still correspond to barren landscape, 0 to 1 values indicate grass and shrubland, and anything above 1 corresponds to high density vegetation. While Figure 10 shows immense amounts of vegetation loss, the mean EVI value for 2013 was 0.96359 and 0.91381 for 2016 (Figure 11). These values do not signify major loss, even though there was a 0.04978 decrease in average EVI, and a noticeable spike in values around 0.4 for 2016 (Figure 11).

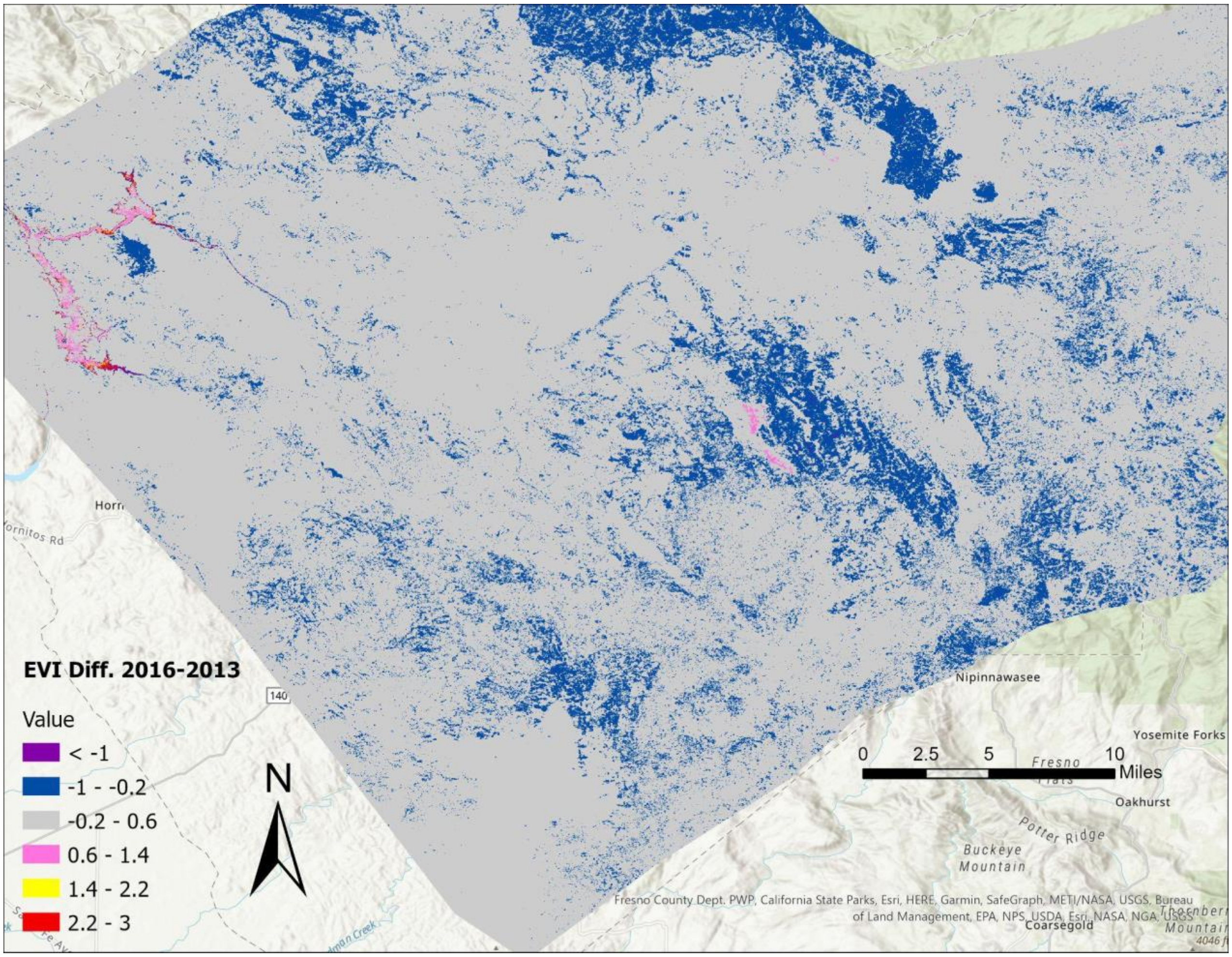
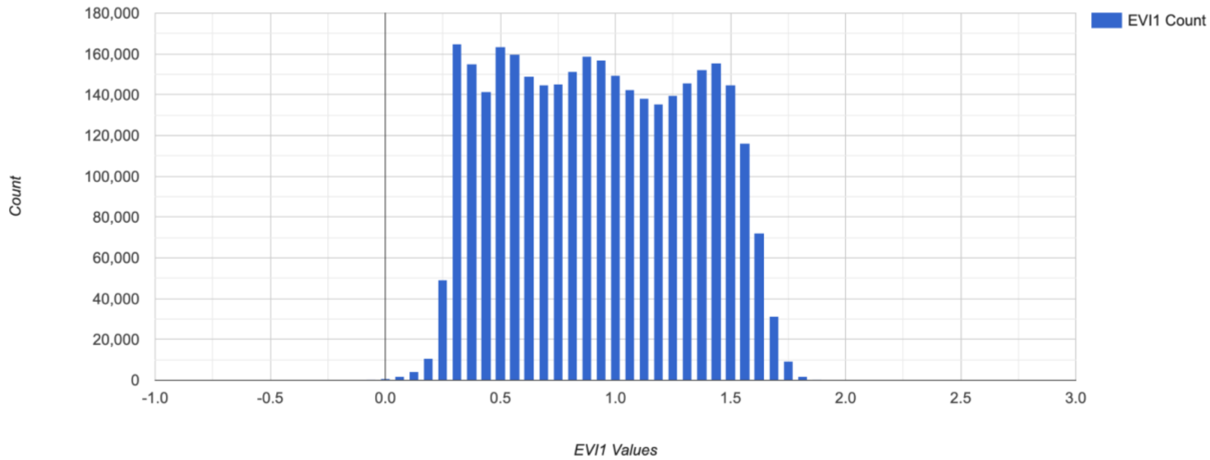


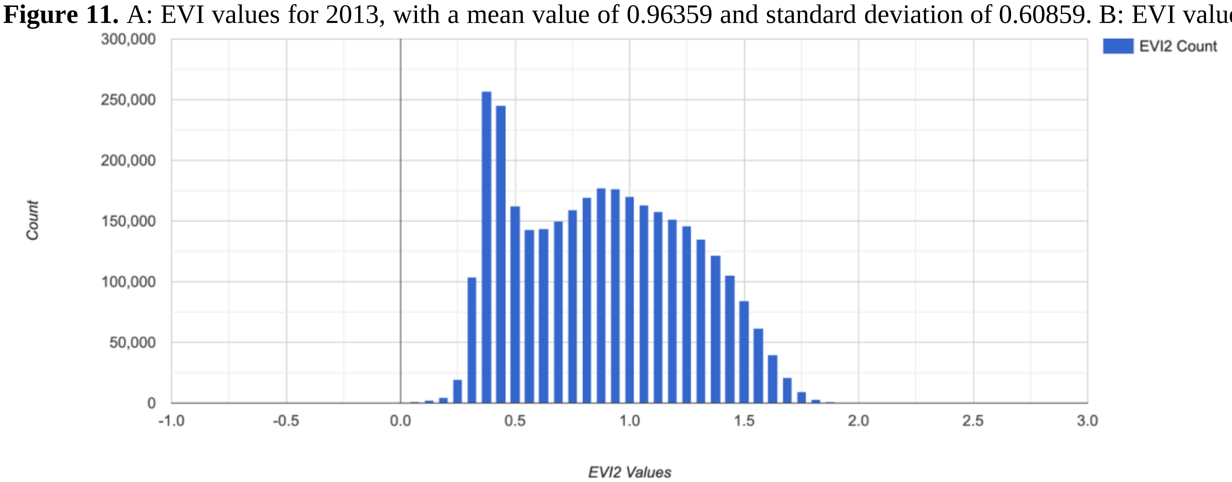
Figure 10. Map of ΔEVI. Source: Author 2023

(A)



(B)

Figure 11. A: EVI values for 2013, with a mean value of 0.96359 and standard deviation of 0.60859. B: EVI values



for 2016, with a mean value of 0.91381 and standard deviation of 1.04103. Source: Author 2023

The results from the LandTrendr application for EVI also show that the same pixel as NDVI experienced the disturbance starting in 2013 (Figure 12). The loss lasted about a year and had a magnitude of roughly 0.75 on the EVI scale (Figure 12). The area maintained a value of 0.5 for another year, seeing no new growth until 2015, when the portion of land began to recover and gained 0.2, then beginning to stabilize.

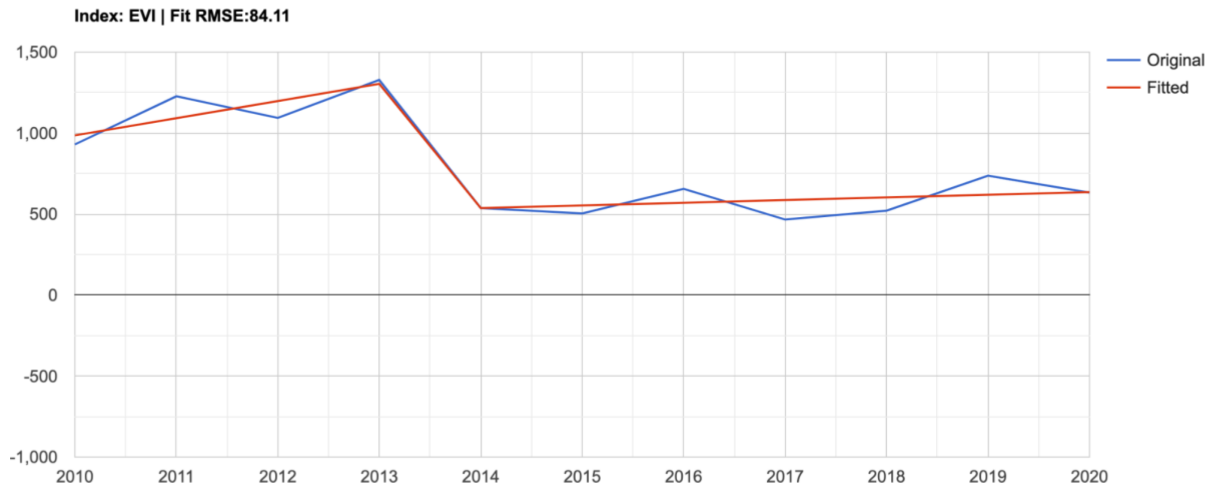


Figure 12. EVI LandTrendr Pixel Time Series analysis of drought affected pixel (same pixel as NDVI's LandTrendr). Source: Author 2023

DISCUSSION

In this study, a multi-index approach is expressed for observing Sierra Nevada ecosystems and vegetation change in response to drought disturbance. The coupling of water and greenness estimates obtained from multispectral Landsat images is the crucial factor in this analysis. Changes that occur gradually and continuously, such as browning from drought and phenological alteration are harder to identify using observations derived from space. These types of disturbances have a relatively low intensity, which necessitates long-term observation series before any signs of disturbance can be detected. All of the indices analyzed recognized an overall loss in their perspective measurements, even if they were minimal. Using both Google Earth Engine and LandTrendr helped solidify the notion that even when a majority of an area experiences loss due to drought, there will always be locations that either resist or are unaffected by the disturbance.

NDWI

The NDWI monitoring water content within plant structure found that the majority of the county experienced no significant change, with a near equal ratio of loss to gain in areas that did encounter alteration. These findings suggest that the index was not able to track the overall drought disturbance as well as NDVI or EVI because there was not as much loss detected. However, Gu et al. 2007 tested NDWI as a drought indicator and found that NDWI values exhibited a quicker response to drought conditions than NDVI. The Gu et al. 2007 study monitored drought in Great Plain grassland territory, which expresses differences in water content, vegetation greenness, and drought conditions compared to Sierra Nevada ecosystems. Unlike NDWI, NDVI has a restricted ability to retrieve information on vegetation water content because it provides data on vegetation greenness (chlorophyll), which is not directly or uniformly associated with the amount of water present in the vegetation (Ceccato et al. 2002). It is safe to say that since NDVI and EVI are vegetation indices and NDWI is a water index, they are estimating different metrics. This means that while NDWI was not as sensitive or responsive to this drought as these other two indices, every drought and ecosystem condition is different and may hold NDWI in higher regards as a drought indicator.

NDWI tracking water content within bodies of water showed an immense amount of loss where there were rivers and lakes, but a decent amount of growth in non open water features. These results imply that NDWI did an excellent job of identifying drought in the areas that it specializes in, however the index provided confusion when monitoring areas with vegetation. Even though the map showed growth in vegetated terrain, the histograms still identified that the majority of the land was under drought conditions. Rokni et al. 2014 found that the NDWI has superiority and higher performance compared with other indexes for the extraction of surface water from Landsat data, with NDVI providing the next highest accuracy. My results agree with Rokni et al. 2014's findings that NDWI is the best index for observing disturbance to open bodies of water, as the other indices mostly looked at vegetation. Since NDVI is more sensitive for green vegetation and NDWI is more sensitive for water covers, a combined approach with NDVI and NDWI is feasible to identify and estimate the land cover changes after disturbance events (Ahmed and Akter 2017). Considering that NDWI doesn't measure vegetation contents, but does an excellent job of identifying change in water systems, I believe that it is crucial to combine a vegetation index with NDWI when observing drought impacts.

NDVI

The NDVI results illustrated that there was extensive loss of green vegetation over the entire Mariposa County, detecting very minimal growth. The identified areas of growth were in the exact same locations as the recognized region of loss from the NDWI index looking at open water features, meaning that the only growth was due to vegetation replacing previous sections of water. These findings indicate that NDVI is a strong and promising index for identifying drought disruption in Sierra Nevada ecosystems, especially when monitoring vegetation. According to Lyon et al. 1998, the NDVI exhibited the highest performance among the Vegetation Indices for detecting land cover changes due to drought in the biologically complex vegetation communities of Chiapas, Mexico. However, in an ecologically diverse vegetation community in North Carolina, Lunetta et al. 2006 found that two-date NDVI differencing and Multiband Image Differencing were ineffective in detecting land cover changes. Many studies observing the effectiveness of NDVI as either a drought indicator or land cover change metric in general have differing outcomes. This is due to the fact that NDVI can change in validity based on varying conditions such as vegetation density, atmospheric scattering, soil reflectance, etc. There is no one clear index when it comes to tracking drought disturbance, however, for the 2013 to 2016 drought in California, the NDVI was extremely effective in examining drought effects on vegetation greenness.

EVI

The EVI portrayed very similar results to NDVI, as they are both vegetation indices, with major vegetation loss spread throughout the landscape and a handful of growth locations around bodies of water. These results suggest that EVI is also a robust and functional index for detecting drought disturbance in the diverse ecosystems of the Sierra Nevadas. For forests where NDVI is often saturated, EVI and other vegetation indices have been used to monitor droughts in the same manner (Brando et al. 2010). I argue that EVI is slightly more effective than NDVI in this scenario, primarily due to its superior sensitivity in high biomass regions. Although this sensitivity is not immediately evident from the Figure 10 map, it is apparent from LandTrendr, where the index's responsiveness is illustrated in the Pixel Time Series graph (Figure 12). The EVI demonstrates a much more rapid response than the NDVI, as evidenced by a comparison of the two graphs (Figures 12 and 9). While the pixel analyzed was severely impacted by drought, in areas with less severe impact, the EVI detects a decline in vegetation even when the NDVI shows little to no change.

Limitations and Future Directions

I identified EVI as the best index in this study to observe drought impacts, with NDVI as a close second, however, as previously discussed, this statement can only be applied to areas of land with the same ecosystems and drought conditions. As much as I would like to help people conduct drought research in other areas of the world, I cannot be certain that EVI will have the same effectiveness for their study. Regardless, the design of this study can still provide framework and feedback to others who are also tracking drought and its impacts. The disadvantage of vegetation index-based drought monitoring is clear, climate conditions other than drought will also reduce vegetation health (Peters et al. 2002). One of the other main drawbacks that I struggled with when processing the index data was the fact that the indices picked up other kinds of disturbances that led to loss, such as fires. I was able to avoid major burns, specifically the Rim Fire, so that the vegetation and moisture loss would not affect my analysis, however, I did not know the whereabouts of smaller unidentified fires, which could have been taken account of. The last major limitation of the experimental design was that there was no statistical analysis run on the data. I needed to find index values from randomly chosen pixels for pre and post drought time periods to see if there were indeed statistically significant results. This would allow me to put more weight into my conclusions and identify if all of the indices were statistically significant, or if there was one that stood out from the rest.

When looking to further develop this experiment, I immediately gravitate towards investigating more indices to see their response in a situation such as the 2013 to 2016 drought. Noteworthy indices that would be interesting to test as drought indicators include normalized difference drought index (NDDI) and standard vegetation index (SVI), as they combine multiple bands and are vegetation based. From here, I would want to see how these indices reacted to the same type of vegetation ecosystems but in different drought and climate conditions, in order to grasp on any trends in similar vegetation types and indices. I am also curious if testing these same indices in a similar climate environment, but with a different vegetation makeup would yield results showing patterns for relationships between indices and climatic settings. This future work has the possibility of helping to create a guide to indices as drought indicators of where and when to use them, a literature review would also be helpful when combining multiple experimental designs.

CONCLUSION

This investigation of a four year span within Mariposa County has proven that drought events cause vegetation and water availability disturbances due to prolonged dry periods. NDVI and EVI identified where drought disturbance was responsible for altering the ecosystem's vegetation cover, where NDWI was better at detecting surface water change, along with some temporal variation in vegetation. When in conjunction, the estimates from these indices can shed light on changing ecosystem conditions, provide insights for long-term drought preparedness plans, determine the optimal timing for water conservation proposals, and help in managing rangeland and agriculture responses. While drought is still inherently difficult to track, I hope the design of this study proves to be helpful, especially when looking into future land use planning for better land management and resource extraction.

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