Post-fire Vegetation Recovery for the Douglas Fire Complex, Oregon (2013)

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Introduction

In recent years, wildfire frequency and intensity has risen in the western United States compared to historic records (Abatzoglou and Williams, 2016). Wildfires can affect many Earth system processes, including hydrologic and sediment erosion, through the removal of vegetation. Some ecoregions will see the development of hydrophobic soil layers that can contribute to the initiation of debris flows (DiBiase and Lamb, 2019; Hubbert et al., 2012). Additionally, the removal of vegetation can lead to hillslope instability. Vegetation stabilizes hillslopes by anchoring the soil with complex root systems, as well as creates sediment "dams" that hold soil on the hillslope up slope of the vegetation (DiBiase and Lamb, 2013. When vegetation is burned during the fire or when burned dead trees fall years after a fire these sediment dams will release material downslope (Roering and Gerber, 2005). Burn severity, topography, vegetation type, and post-fire vegetation management can all influence vegetation recovery rates.

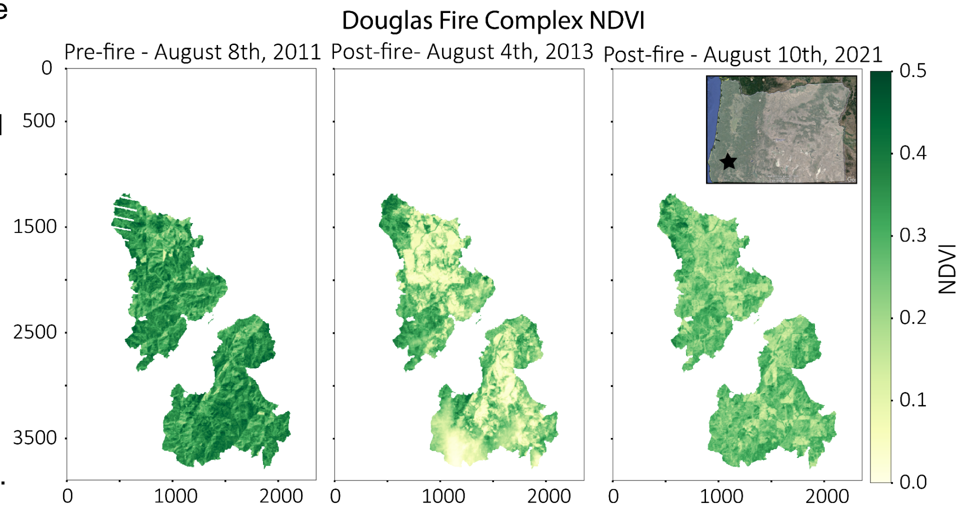

Figure 1: Douglas Fire Complex NDVI changes over time. From left to right, NDVI images from 2011, 2013 (after the wildfire), and 2021. In 2013 land management boundaries can be seen in the north portion. As more time passes since the fire, the land boundaries are becoming less visible. Inset - Douglas Fire Complex location if southwestern Oregon Marked by black star.

In 2013, a lightning strike ignited the Douglas Fire Complex, which covered 19,760 ha of land in southwestern Oregon, USA (inset figure 1). This fire not only covered a topographically complex region, but a landscape characterized by highly contrasting timber harvesting practices resulting in forests with differences in stand density and underbrush coverage. Bright et al. (2019) demonstrated that burn severity and vegetation makeup influenced the rate at which vegetation recovered through normalized burn ratios (NBRs). In the Douglas Fire area Privately owned land experiences frequent clear cuts and replanting of trees in higher density stands when compared to land managed by the Bureau of Land Management (BLM). Zald and Dunn (2018) found that the best predictor for predicting burn severity in the Douglas Fire was land management. Furthermore, they found that privately owned lands burned more severely on average compared to those managed by the BLM. However, this study looked at only the initial burn severity measurements and another study has not been done yet about how this contrast in burn severity in land management regions has influenced the rate at which vegetation recovers.

To investigate the question of how quickly vegetation regrows in topographically complex regions after wildfire, we created and analyzed normalized difference vegetation indices (NDVI) from landsat 7 and 8 images using Google Earth Engine. We looked at how the spread, median, and mean NDVI values changed over time as well how quickly vegetation returns to a "pre-fire" state through percent difference from pre-fire NDVI averages. Furthermore, we looked at how contrasting timber harvesting practices influence the rate at which vegetation recovers.

Methods

Landsat 7 & 8 image collection

To collect landsat images of the region of interest, we used a script with Google Earth Engine through Google Collab To capture a full picture of before, during and after the fire, we downloaded images from 08/23/2011 to 01/30/2022. To avoid cloudy days that would depreciate the quality of the images, we limited our collection to images with less than 30% cloud cover. These parameters returned 99 images, although 7 were from a neighboring Landsat path/row and were discarded.

Douglas fire area and land management tifs

We used land ownership and burned area GeoTIFFsfrom Zald and Dunn (2018) to separate out private and publicly managed land as well as fire extent. To make ownership and fire extent tif files compatible with our Landsat images, we projected them into the same coordinate reference system (CRS) as the Landsat images, as well as increase their spatial extents to match the Landsat images. The Landsat images CRS was ESPG:32610, or UTM zone 10N. No data values were used when padding the spatial extents of the two files.

NDVI analysis

To analyze our Landsat images, we wrote several functions in python through Jupyter Lab. The first function imported each Landsat image and created a NDVI image of the data. Then, those NDVI images were clipped based on the Douglas fire area mask file and exported as a new GeoTIFF to a separate folder. The second function was a helper function to create a list of dates from the images, in order to have an accessible data structure to plot against further on in the analysis. The third function imported the clipped NDVI images and separated them based on the binary land management GeoTIFF file, then saved the results into two 3-dimensional arrays, where the first two dimensions are spatial and the third dimension is time. Lastly, we created another helper function to begin our analysis

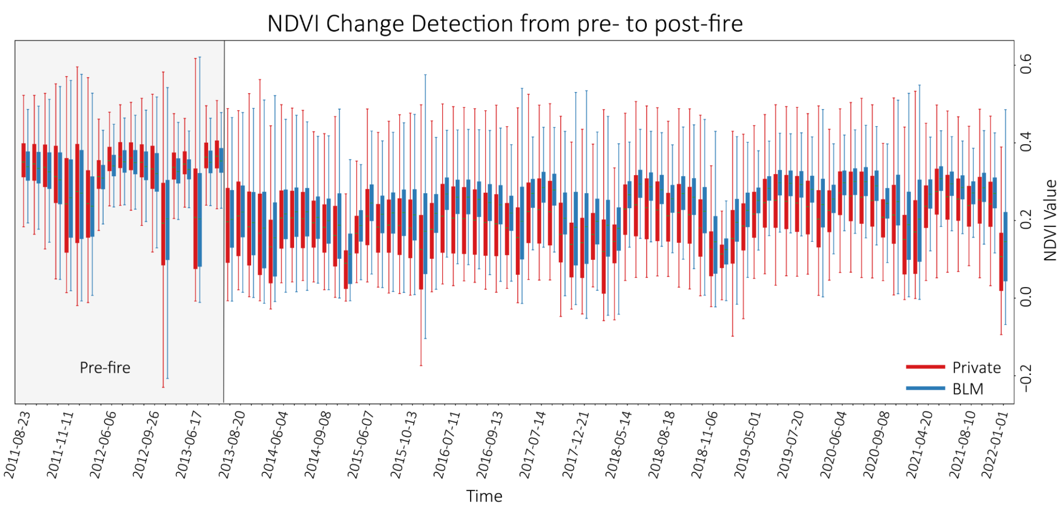

Figure 2: Boxplots of pixel NDVI values for each time step. Blue represents pixels that reside in BLM managed land, while red represents pixels in privately owned land. Pre-fire time steps (occuring in the transparent gray area) have higher NDVI values on average. A clear drop in NDVI values occurs after the Douglas Fire in 2013.

and start plotting. This function flattens these two 3-dimensional ownership arrays while discarding any no data entries present. From here we used two main plots: a boxplot and a post-fire mean value trendline. Other analyzes that we think could be useful are discussed in the Discussion section.

Results

In Figure 2, the results of our script can be seen in boxplot format. The NDVI values are sorted by date and colored based on land ownership. As expected, directly after the fire in 2013, there is a sharp decrease in NDVI values for both private and BLM managed lands. To better understand the relationship between land ownership and vegetation recovery, we pulled the mean values and standard deviations from the data, and fit a linear trendline to the means (Figure 3).

From this, we consider that the slopes of these trendlines might have some relationship to overall recovery rate. In a rough estimate of the time it will take these areas to recover to pre-fire values, we can solve these equations for a given pre-fire value. With an estimated pre-fire NDVI value of 0.3, we estimate the BLM managed land would recover to pre-fire values roughly four years before the privately managed land. There are many caveats to this back-of-the-envelope calculator. We're assuming a pre-fire value of 0.3 for every pixel in the region, while natural landscapes have a range of NDVI values even when the vegetation is healthy. Furthermore, we're assuming a timescale interval of months when solving the linear equation (using months for our *x* variable), which is near our Landsat time scale interval, but not close enough for any sort of accurate calculation.

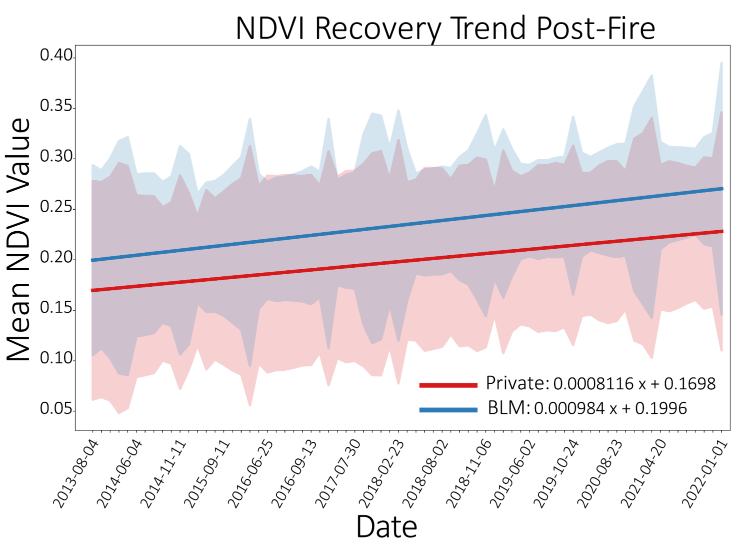

Figure 3: Post-fire mean and standard deviation of NDVI values over time. The slopes indicate that the landscape mean NDVI on BLM land is recovering at a *slightly* faster rate than the privately owned land.

Discussion and future work

Although there is work that has done similar analysis on vegetation recovery after wildfire and remote sensing, this project could be potentially interesting since it is at a local scale,

One thing we learned from preliminary work on this project is that sampling every image that exists from 2011 to now (so about 1-2 images per month) is too many to do meaningful analysis of the data (also takes up a lot of space). Furthermore, seasonality (and thus serial correlation) make it difficult to properly interpret results. One idea we have so far to address this is to average the "growing season" or spring, summer, fall, and winter images together.

To begin to test how we might present or analyze this data in the future we plotted percent differences for images in our dataset that were collected in July (figure 4). Pixels in pre-fire images (July 3 and 19th in 2013) were averaged to create a "pre-fire" raster. Then for each time step, we calculated a percent difference from pre-fire for each pixel. Here we see pre-fire july months in 2013 as similar to one another. As expected, after the fire we see a clear jump in percent differences indicating that immediately after the fire there is a large difference in NDVI compared to pre-fire conditions. As time since fire increases, we see the decline of median percent differences values for both private and BLM areas. This indicates that the differences between the current state and the pre-fire state are getting closer (as values approach zero).

However, it does appear (visually- no statistical tests done yet) that the spread of BLM pixels at each time step is smaller than private land and is approaching a pre-fire state more rapidly.

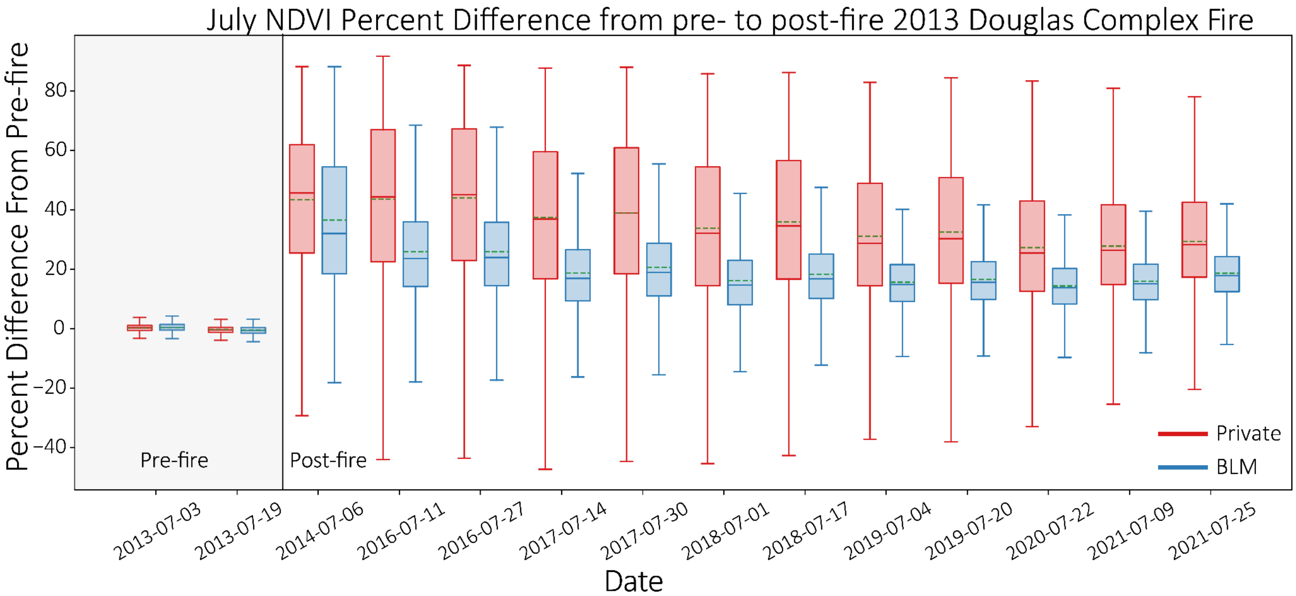

Figure 4: NDVI "percent difference" for the month of July. Pre-fire (gray box) NDVI values throughout the rasters are similar in median and spread to one another. Blue boxes represented the spread and median of percent differences for all pixels in a time step located in land managed by the BLM. Red boxes represent the land managed by private companies.

Furthermore, this NDVI analysis (or a more in-depth and rigorous analysis of this) will be helpful to supplement preliminary change detection research done by Brooke Hunter with a time series of LiDAR analysis. Preliminarily, this work demonstrates the largest hollow evacuations (debris flows) measured by average incision depth occurred in privately owned land. Connecting the timing, magnitude, and style of post-fire erosion to land management and vegetation recovery could have important implications for how wildfires affect not only ecosystem properties but hazards, such as debris flows and landslides, as well.

GitHub Link

Hunter, B., Sheppard, J., 2022. Postfire_NDVI. https://github.com/bhunter2/PostFire_NDVI

References

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