Elevation, Aspect and Slope Do Not Effect the Rate of Vegetation Recovery Following a Wildfire

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Abstract

Future changes in climate like increasing temperatures and decreasing precipitation rates are expected to increase wildfire incidents in the US. Understanding the factors that influence post-fire vegetation recovery is an important step for forest management authorities to aptly allocate resources and evaluate land management efforts. Researchers have attempted to find a relationship between topographical factors such as elevation, slope and aspect, and the rate of vegetation recovery following a wildfire. While some studies have found correlations, the results are conflicting in the case of elevation and are statistically unconvincing in the case of aspect. The purpose of my research is to study this potential relationship by using four different fire incidents as case studies. All four fires occurred in the summer of 2002, all were located in Utah, and all were larger than 5000 acres. For each fire, I conduct a spectral analysis of 15 Landsat Thematic Mapper 5 images, from 1994-2008, in order to determine whether there is a statistically significant effect of topographical factors such as elevation, aspect and slope, on the rate of post-wild-fire vegetation recovery. My analysis reveals an inverse exponential trend in the percentage recovery following the fire, and concludes that there is no statistically significant and consistent relationship between these various topographical variables and the rate of recovery.

Key Points:

1. Post-wildfire vegetation recovery follows an inverse exponential trend, with rapid recovery in the beginning and slower recovery in subsequent years.
2. Elevation, slope and aspect have no significant effect on the rate of post-wildfire recovery.

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1 Introduction

Every year, forest wildfires are accountable for burning 4-5 million acres of vegetated land in the United States (Thiessen, 2018). Politi et al. (2009) predicts that changing climatic conditions, particularly increased temperatures and decreased precipitation, could make forests more susceptible to wildfires in the future. According to data from the National Interagency Fire Center (NIFC), there has been an increase in the number of acres burnt in US wildfires since 1980 (Hausfather, 2018).

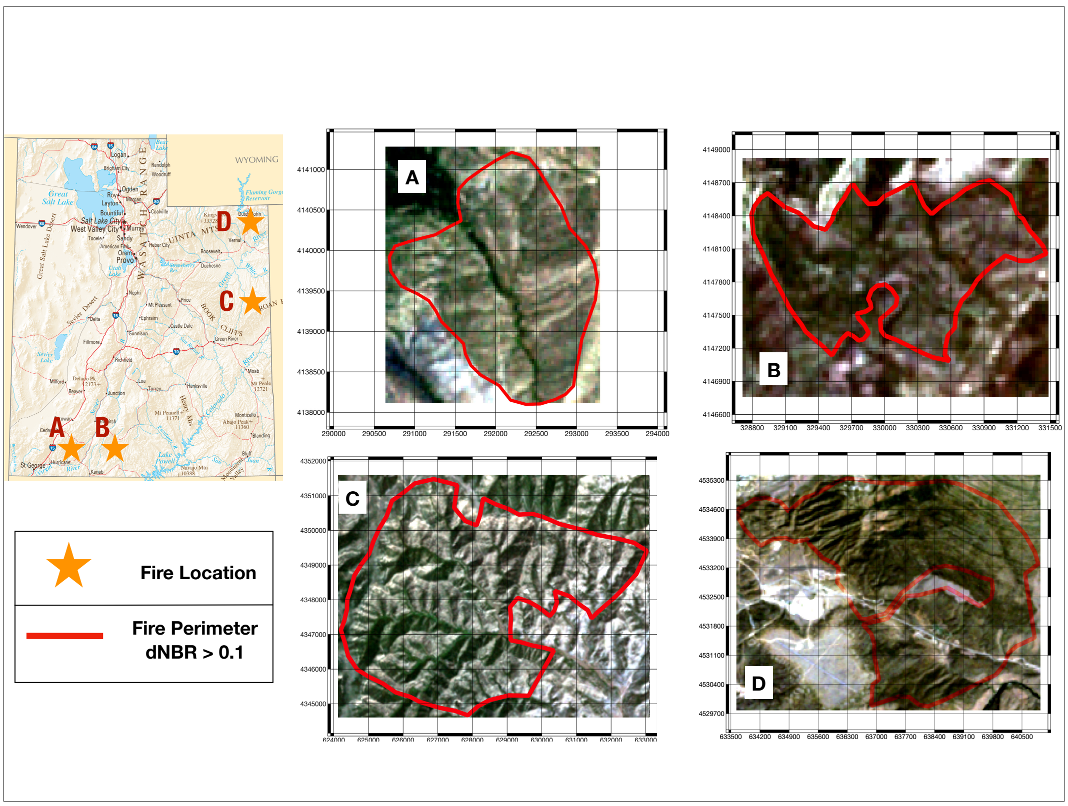

Figure 1: True-color maps for the fires at (A) Mill Creek, (B) Deep Creek, (C) Diamond Ridge and (D) Dutch John Mountain

The study of the effect of topographical factors on post-wildfire vegetation recovery dynamics has been the focus of several studies in the past (Dodson & Root, 2013; Ireland & Petropoulos, 2015; Malak & Pausas, 2006; Miranda et al., 2016; Potter & Hugny, 2018). Such studies aim to build an understanding of the factors affecting post-wildfire recovery patterns in order to help forest management authorities in effectively responding to wildfire occurrences (Ireland & Petropoulos, 2015; Petropoulos et al., 2014). Forest management authorities can use this information to a) identify regions that have naturally slow recovery rates and therefore require more attention and care, and b) evaluate the effectiveness of previously employed land management techniques.

Several studies that aimed to assess the effect of aspect on post-wildfire recovery have reported that north-facing slopes recover faster than south-facing slopes (Ireland & Petropoulos, 2015; Mouillot et al., 2005; Petropoulos et al., 2014). The reason for this might be because north-facing slopes retain more moisture than south-facing slopes, and therefore are better suited for vegetation growth and recovery (Ireland & Petropoulos, 2015). However, some of these studies base their conclusion on results and methods which are not very statistically convincing. For example, Ireland & Petropoulos (2015) used a dataset that consisted of only 6 Landsat images spanning 8 years, derived from Landsat 5 and Landsat 7 interchangeably even though previous studies have found calibration discrepancies in the results between Landsat 5 and Landsat 7. (Liu et al., 2016; Vogelmann et al., 2001). Additionally, the difference in mean Normalized Difference Vegetation Index (NDVI) values for north-facing slopes and south-facing slopes that Ireland & Petropoulos (2015) base their conclusion on is much smaller than the standard deviation of their values, which makes the results statistically insignificant. Similarly, in Petropoulos et al. (2014), the data set consisted of only 5 Landsat images, and differences in mean NDVI at different aspects were smaller than the standard deviation.

In the case of elevation, several studies have used remote sensing techniques to show that vegetation recovery at lower elevations is faster than recovery at higher elevations. For example, Zhao et al. (2016) studied wildfire recovery in the Greater Yellowstone Ecosystem with elevation ranges of 1400m - 2300m and Sass & Sarcletti (2017) studied wildfires in the Northern European Alps covering elevations from 800m - 2200m. Both studies concluded that vegetation recovery is faster on lower elevations than on higher elevations. However, other studies have shown elevation gradients to have the very opposite effect. For example, Dodson & Root (2013) studied wildfire recovery in ponderosa pine forests in Oregon with elevations ranging from 641m to 1368m and Lippok et al. (2013) studied wildfire recovery in the Andes with elevations ranging from 1950m - 2500m. Both studies found that higher elevations had a better recovery than lower elevations. One possible reason behind this could be that with increasing elevation, decreased temperature and increased precipitation counters the hot and dry microclimates created at burnt sites, facilitating regrowth and recovery (Dodson & Root, 2013).

In the case of the effect of slope on wildfire recovery, most studies agree that steeper slopes recover slower than flatter slopes due to greater surface run-off and erosion at steeper slopes. Malowerschnig & Sass (2014) studied a slope range from 0-65 degrees in Styria, Austria and Sass & Sarcletti (2017) studied a slope range from 0-79 degrees in the Northern European Alps and both revealed slower recovery on steeper slopes. With this context, the main aim of my study was to determine whether there is a significant and consistent effect of any of these three topographical variables, i.e. elevation, aspect and slope, on the rate of post-wildfire recovery across fires in Utah.

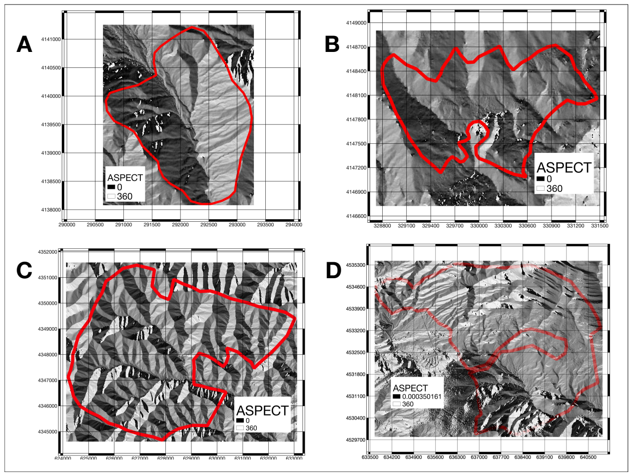

Figure 2: Aspect maps for the fires at (A) Mill Creek, (B) Deep Creek, (C) Diamond Ridge and (D) Dutch John Mountain

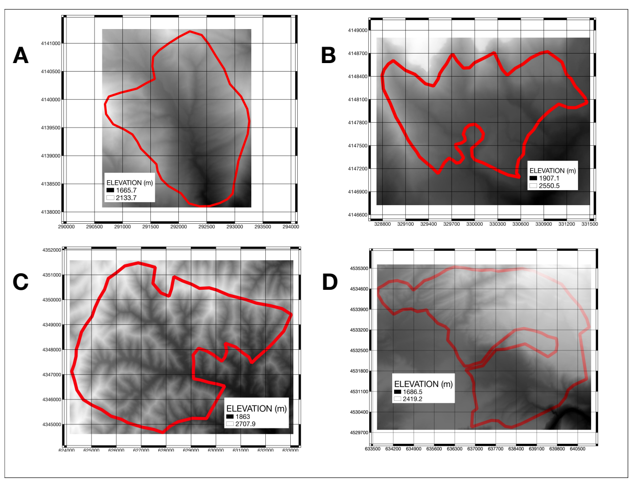

Figure 3: Elevation maps for the fires at (A) Mill Creek, (B) Deep Creek, (C) Diamond Ridge and (D) Dutch John Mountain

My study sites consisted of four large fires that occurred in Utah in 2002. Each of these fires was a class G fire, i.e. it burnt more than 5000 acres of land. The first fire occurred in Mill Creek, and the second in Deep Creek, both in southwestern Utah. The third fire burnt Diamond Ridge, in eastern Utah and the fourth fire burnt the Dutch John Mountain area in northeastern Utah. Figure 1 shows the true-colour images of each of these four sites and their locations on the map of Utah. Figures 2-4 show the ranges in aspect, slope and elevation at each of the four sites. All four of these sites had a complete 360-degree variation in aspect, a variation of at least 600m in elevation in the range of 1600m - 2600m, and a range of slopes from 0-degrees to above 50-degrees. This variation in all

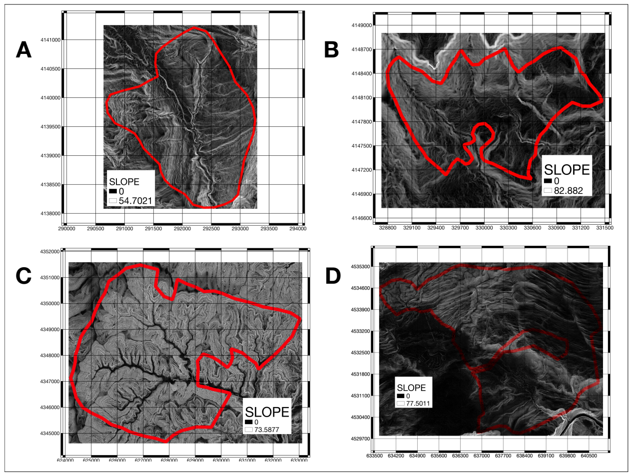

Figure 4: Slope maps for the fires at (A) Mill Creek, (B) Deep Creek, (C) Diamond Ridge and (D) Dutch John Mountain

three topographical factors made all four of these sites suitable for studying post-wildfire recovery dynamics.

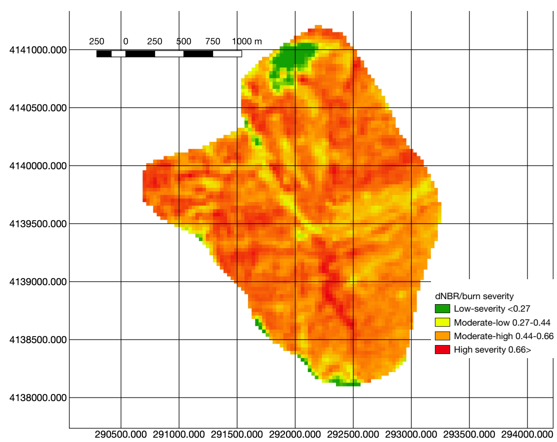

Figure 5: dNBR severity map for Mill Creek 2001-2002.

2 Data and Methods

For each of the four study sites, I used a total of 15 Analysis Ready Data (ARD) Landsat Thematic Mapper 5 images, with 30m pixels, one from each year from 1994 - 2008. I downloaded all the images from the United States Geological Survey (USGS) archive ref. To avoid calibration discrepancies, I used only Landsat 5 images in my study and disregarded images taken from Landsat 7. I made sure the images had no cloud cover and to control for the seasonal changes in vegetation, I tried to get most of my images from August each year. However, not all years had a usable image from August. For these years, I did a seasonal correction which I will explain shortly. In order to avoid georeferencing problems with the Landsat 5 images, I reprojected each image onto a common Coordinate Referencing System (CRS), specifically EPSG:32612, i.e. WGS 84/UTM zone 12N, which is the UTM zone for Utah.

Landsat 5 detects 7 different wavelengths of light, including RGB, NIR, Thermal and SWIR. Several indices have been developed and extensively used to identify spectral signatures of different land cover types. (Petropoulos et al., 2014; Veraverbeke et al., 2010). The Normalized Burn Ratio (NBR) incorporates the short-wave infrared (SWIR) band of the spectrum (Norton, 2006), as described in Equation 1.

$$NBR = \frac{NIR - SWIR}{NIR + SWIR} \tag{1}$$

To determine the burn perimeter of the study patch, I computed the delta-NBR (dNBR) on the Landsat images I found closest to the start and end dates of the fire(2001/08/11 and 2002/08/14), as described by Equation 2

$$dNBR = NBR_{pre-fire} - NBR_{post-fire} \tag{2}$$

I used the resulting burn severity map to visually identify the burn patch. To quantitatively verify that my shapefile included only burnt areas, I checked my raster layer statistics for the defined patch to make sure no part of the area was unburnt, i.e. no area had a $dNBR < 0.1$ which has been shown by (Norton, 2006) to be the threshold value for distinguishing between burnt and unburnt areas. This burn severity map for the fire in Mill Creek can be seen in Figure 5.

After clipping the Landsat scenes along the burn perimeter, I computed the and NBR rasters for each image. At this point, I corrected for seasonal differences between the Landsat images, because as mentioned earlier, images from August were not available for all years. I searched for the years in my study period with the most number of Landsat images available. 1996 and 1997 had monthly images from May - November. I computed the NBR rasters for each of these monthly images. Next, I computed the mean NBR of each monthâs raster in 1996 and subsequently computed its difference from mean NBR in August 1996. I, then, repeated the same steps for 1997. For each month, I computed the average deviation from the NBR in August. In the final Landsat images that I used for each year, when I could not find a Landsat image from August, I subtracted/added this mean deviation values from the entire NBR raster for the year, depending on the month it was from.

All my topographical data was obtained from the Utah Automated Geographic Reference Center (AGRC). I downloaded 5 meter Auto-correlated Digital Elevation Model (DEM) tiles that covered each of the four sites and used the DEM to compute slopes and aspects.

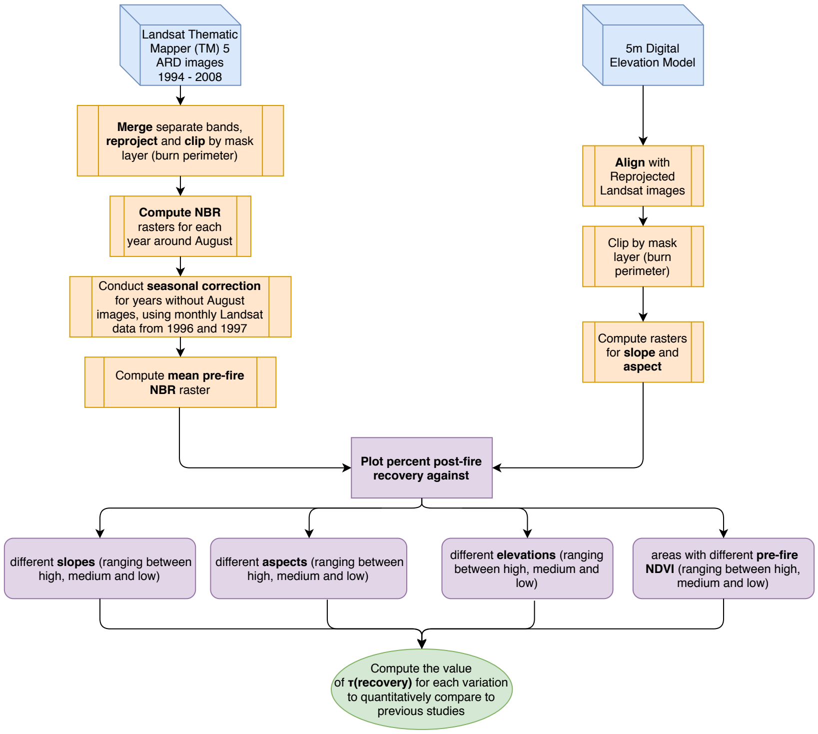

Figure 6: Flowchart to describe the work flow of my method. This method was repeated for each of the four sites

Using the yearly NBR rasters from 1994-2001, I calculated the mean pre-fire NBR for my site. I divided the pixels in each image according to the range in slope, elevation and aspect, and pre-fire NBR. I refer to the top 33 percentile as high, middle 33 percentile as medium, and bottom 33 percentile as low for each variable. I then plotted the mean NBR for each of these pixels for each year as seen in Figure **??**. Additionally, I plotted the percentage recovery for each variable, as a fraction of its original pre-fire NBR according to the following equation()

$$NBR_{change} = mean\,NBR_{pre-fire} - NBR_{fire-year} \tag{3}$$

$$\%\,recovery = \frac{NBR_{post-fire}}{NBR_{change}} * 100 \tag{4}$$

The recovery trend looked roughly exponential, so I tried to fit an exponential curve on it using Equation 5

$$y = b_1 - b_2 e^{-b_3 x} \tag{5}$$

where $y = \%\,recovery$ and $x = years\ since\ the\ fire$.

I calculated the R^2 values for each of the exponential fits according to Equation

$$R^2 = 1 - \frac{var(residual)}{var(data)} \tag{6}$$

Where the $residual = data - fit$

I then computed the $\tau_{recovery}$ for the exponential fit, where $\tau_{recovery} = \frac{1}{b_3}$ from Equation 5 in order to quantify the dependence of the rate of recovery on each of the 4 variables. In simpler terms, $\tau_{recovery}$ is the time taken in years to achieve $\frac{1}{e} * 100\%$ = i.e. 37% of the original pre-fire NBR. A faster recovery will correspond to a steeper exponential fit and a smaller $\tau_{recovery}$ value. Figure 6 provides an overview of the methods I used in this study.

3 Results

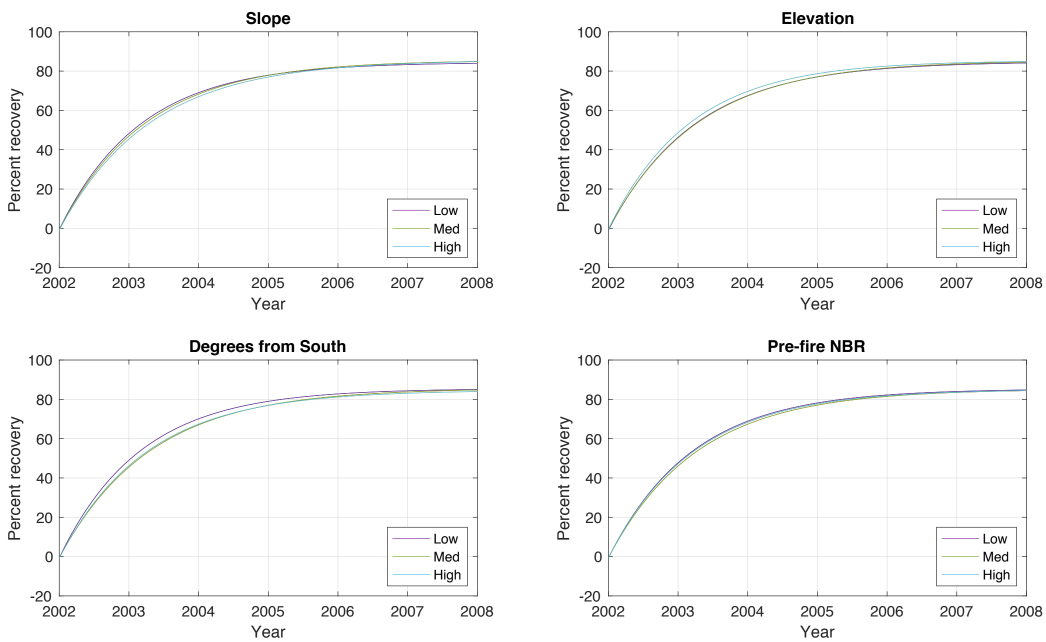

Figure 7: Percent recovery exponential fit at varying, i.e. low, medium and high, slopes, elevations, aspects and Pre-fire NBR. Notice that all three curves for each variable are very similar, and therefore represent a very similar rate of recovery. Ideally I would add annotations to the figure if I had a bit more time. This figure is from the analysis on the fire in Mill Creek. For the figures for the other three fires, please refer to the Appendix.

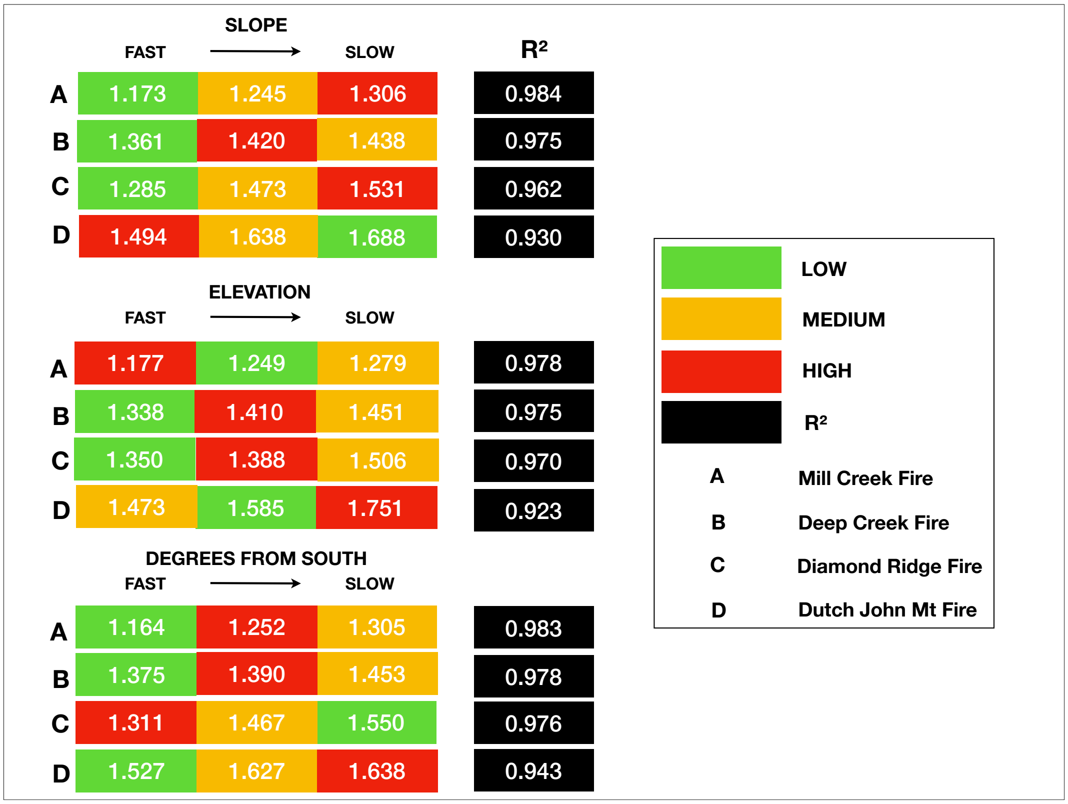

Figure 8: $\tau_{recovery}$ values corresponding to each topographical variable arranged in ascending order, i.e. fastest to slowest, for the fire in (A) Mill Creek, (B) Deep Creek, (C) Diamond Ridge, and (D) Dutch John Mountain. Notice that none of the results line up, indicating that the small differences in $\tau_{recovery}$ values do not represent a consistent trend across fire. In other words, even though low (flatter) slopes recover faster than high (steeper) slopes, by a difference of around 0.1 years, even that tiny difference is not consistently seen across fires. The high R^2 values indicate that my fits had a high reliability.

4 Discussion

Figure 8 shows the $\tau_{recovery}$ values corresponding to each topographical variable at low, medium and high values for each of the four fires. As seen in the figure, the small differences in $\tau_{recovery}$ values do not represent a trend across the four fires for any of the three variables. The previous studies on the effect of these topographical factors on the rate of post-wildfire recovery that I mentioned in the beginning did not use $\tau_{recovery}$ as their metric for determining their results. Both Ireland & Petropoulos (2015) and Petropoulos et al. (2014) used differences in post-fire mean NDVI as a measure of post-fire rate of recovery. For example, Ireland & Petropoulos (2015) reported a mean NDVI increase of 0.042 from 2007 to 2010 on north-facing slopes, and a mean NDVI increase of 0.01 from 2007-2010 on south-facing slopes. Their conclusion that south-facing slopes recover slower was based on the fact that this increase in mean NDVI was smaller for south-facing slopes.

It is important to note here that this difference is not a statistically valid way to correlate these topographical factors with the rate of recovery because it has not been normalized against the pre-fire NBR. As seen in the first section of Figure 9, shows that the highest pre-fire NBR burnt down to the same as areas with lower pre-fire NBR, but these areas recovered again to a higher NBR. The reason for this trend is most likely because the areas with higher pre-fire NBR are generally more conducive to vegetative growth (e.g. lower elevations, less steep and north-facing slopes) (Tao et al., 2018), and therefore sustain a faster regrowth in comparison to areas with less favourable conditions. In contrast, in the second half of Figure 9, after taking into account the pre-fire NBR for each pixel and plotting percent recovery rather than simply mean NBR, it becomes clear that the *rate of recovery to pre-fire vegetation* is similar for all areas. In other words, the reason higher elevations seem to have a lower post-fire NBR is not because they recovered slower, but because they had a lower NBR pre-fire as well, and they simply returned to their original state at a similar rate as other elevations.

The rate of recovery, as is seen by the gradient of the plots in Figure 7, is steeper in the initial years after the fire, and then gets less steep from 2004 on wards. This trend makes sense because the initial recovery need not be recovery of all the same vegetation. In fact, fire that destroys upper canopy vegetation clears room for smaller vegetation to spring up with minimal competition for resources. This shrubbery and lower-storey vegetation regrowth could be fast whereas long-term tree regeneration could take longer.

5 Conclusions

Based on my results, I conclude that there is no significantly consistent difference in the rate of post-wildfire recovery at variable elevations, aspects and slopes. I studied four fire incidences, and all four appeared to have different recovery patterns. Therefore, forest management authorities cannot derive much guidance for managing a particular wildfire incidence by relying on the results from studies conducted on individual fires, which includes most of the studies I mentioned in the beginning. A more informative option for forest managers could be to conduct a more local analysis on their own site using remote sensing techniques to identify areas that may be having stunted rates of recovery.

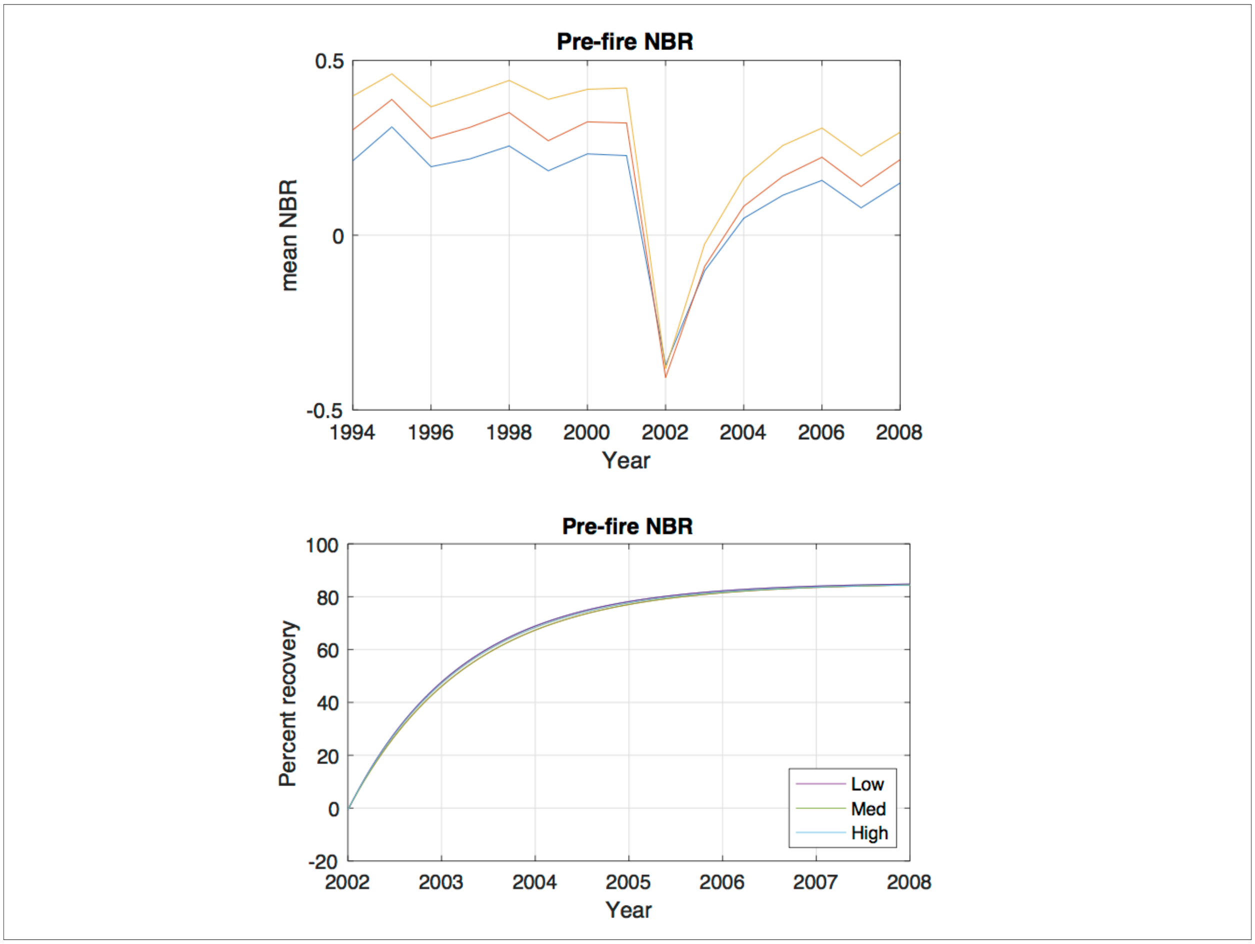

Figure 9: The first figure is a plot of yearly mean NBR for the site at Mill Creek, separated by low, medium and high pre-fire NBR. Notice that areas with high pre-fire NBR burn down to the same value as other areas, but recover one again to high post-fire NBR levels. The second figure is a plot of the percent recovery of the site, once again separated by low, medium and high pre-fire NBR levels. Notice how similar the curves now look, indicating that as a *percentage* of the pre-fire vegetation, all areas recover at the same *rate*.

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