

Using Remote Sensing to Analyze the Effect of the 2015-2016 El Niño Drought on the Forest Health in the Lower Tapajós Region of the Amazon Rainforest

By Valerie Fan

Author Bio

Valerie Fan is a senior at Aragon High School. At school, she pursues her passion for engineering as vice-captain of her school's underwater robotics team and as president of Aragon's Technology Student Association. In order to understand how to engineer for humanity, she explores topics such as the sinking of the Titanic and gets involved in impact-focused initiatives, such as an Amazon Expedition – which encouraged her to explore the Amazon Rainforest even further using remote sensing.

Abstract

Preserving the Amazon rainforest is crucial for maintaining its biodiversity, protecting local communities, and slowing down global warming. Deforestation and anthropogenic climate change have been interfering with the natural ecosystem dynamics and degrading the health of the rainforests. This study seeks to understand the impacts of deforestation on forest health and the effectiveness of restoration efforts in sustaining the rainforests. Leveraging publicly available satellite data, we compared the short-term changes in forest health of intact forests, areas of forest loss, and areas of forest gain in the Lower Tapajós region following the 2015-2016 El Niño. Particularly, a combination of the Normalized Difference Vegetation Index and the Normalized Difference Water Index representing vegetation greenness and water content, respectively, were used as proxies for forest health. We found that intact forests are significantly less vulnerable to drought, with smaller disturbance magnitudes and faster recovery rates compared with most areas of forest gain and forest loss. We also observed that a few areas of forest gain and forest loss showed patterns similar to that of intact forests. Our analyses affirm the importance of preserving intact rainforests to maintain their resilience. Furthermore, our study suggests that carefully managing reforestation efforts and levels of deforestation can improve forest health.

Keywords: Remote Sensing, Deforestation, Reforestation, Anthropogenic climate change, Vegetation Index, Forest Health.

1. Introduction

The Amazon is the world's largest tropical rainforest, consisting of more than 50 percent of all remaining tropical rainforests on earth (Butler, 2020). Not only is it home to an immense amount of biodiversity, but it also provides a critical cooling effect on the planet (National Geographic, n.d.). As a major player in the world's oxygen and carbon cycle (Houghton et al., 2000), the preservation of the Amazon Rainforest is crucial to fighting anthropogenic climate change.

In the Amazon, forests play an important role in maintaining the ecosystem's water cycle. However, deforestation in the Amazon rainforest has directly contributed to worsening drought (Staal et al., 2020). Several extreme droughts have occurred on a much more frequent basis in recent decades, specifically in 2005, 2010, and 2015. In the future, the warmer climate may lead to more frequent and/or intense dry seasons and may also increase the risk of fires, impacting the ecosystem and communities in the Amazon (Staal et al., 2020).

In response to the increasing degradation of the Amazon Rainforest, measures such as early warning systems (Boulton et al., 2013), land-use surveillance (Mainville, 2017), as well as analyses of the resilience of the Amazon (Boulton et al., 2022) have been implemented in order to understand its conditions and slow down further degradation. Particularly, remote sensing through satellite monitoring has long been used to observe the Amazon rainforest (Boulton et al., 2022, Torres et al., 2021, Fragal et al., 2016). Remote sensing techniques make it feasible to quasi-synchronously monitor forest health, an indicator of forest degradation, through the variations in vegetation indices over large spatial and temporal scales. Thus, remote sensing offers efficient complementaries to field and in situ monitoring.

Vegetation greenness – a composite of canopy cover, leaf area, and chlorophyll content – and water content are often used to gauge forest health and stress (Wilson & Norman, 2018; Joiner et al., 2018). The Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Normalized Difference Water Index (NDWI) are proxies of vegetation greenness and water content. They have been previously used in tropical forests

to assist land-cover classifications, detect seasonal phenological changes, assess forest disturbance, and predict forest resilience (Reiche et al., 2018; Zhu et al., 2021; Liu et al., 2021). NDVI measures vegetation greenness via the multispectral reflectance properties of chlorophyll and plant leaves. Specifically, red wavelengths are absorbed by chlorophyll A and B, while near-infrared (NIR) wavelengths are scattered by plant leaves (Costa et al., 2021). EVI is similar to NDVI, but “corrects for some atmospheric conditions and canopy background noise and is more sensitive in areas with dense vegetation.” (US Geological Survey, n.d.). NDWI measures vegetation water content through a combination of Short-Wave Infrared Wavelength (SWIR1: 1.55 -1.75 μm) reflectances and NIR reflectances (Joint Research Centre, 2011).

Leveraging publicly available satellite data and user-friendly data mining and analysis tools, we sought to gain insight into the effects of deforestation on forest health and understand forest restoration efforts in sustaining the Amazon rainforest. Particularly, this study evaluates how extreme drought may affect vegetation greenness and water content in the Amazon rainforest and compares the way in which intact forests (IFs), areas with forest loss (FL), and areas of forest gain (FG), respond to the extreme drought conditions. We hypothesized that the health of areas of FL suffer greater impacts from extreme drought conditions than that of intact forests and areas of FG. In addition, we hypothesize that areas of FG may have the ability to recover to health resembling that of intact forests.

2. Material and Methodology

2.1 Study Region

The Lower Tapajós region in the eastern Brazil area was the Amazonian epicenter of the 2015-2016 El Niño (Berenguer et al., 2021). The extreme drought and wildfires led to the death of around 2.5 billion trees and plants in the area (Hernandez, 2021). A study has also revealed that the mortality of trees in the drought and fire-affected forests continued to be higher than normal for up to 3 years after the extreme drought (Berenguer et al., 2021).

The Lower Tapajós region consists of the Tapajós National Forest, representing the IFs, areas with FL, and FG as shown in Figure 1A. The type of forests was determined using the University of Maryland's Global Forest Change tool (Hansen et al., 2013). A total of 12 sites, 4 of each for IF, FL, and FG, were chosen to observe the effect of the 2015-2016 El Niño on vegetation indices. Their locations and types of each site are listed in Figure 1B.

The Global Forest Change tool defines areas of forest gain as the “inverse of loss, or a non-forest to forest change entirely within the period 2000–2012” (Hansen et al., 2013). Forest cover loss is defined as “a stand-replacement disturbance, or a change from a forest to non-forest state, during the period 2000–2021” (Hansen et al., 2013). Using the forest loss year indicator, we verified that the forest loss in our chosen sites occurred near the year 2000.

2.2 Data Acquisition

Climate Engine is an online platform built from Google Earth Engine in 2014. It is a “no-code” user interface that allows users to easily perform cloud-based computing of climate and remote sensing data, create maps, and generate graphs to visualize various variables. Climate Engine was used to obtain climate data, NDVI, EVI, and NDWI time series.

The mean time series of precipitation (PPT), Climate Water Deficit (CWD), and Palmer Drought Severity Index (PDST) of the study regions were obtained using the TerraClimate-monthly dataset as shown in Figure 2. These environmental variables are commonly used indicators of drought.

The NDVI and NDWI time series were obtained based on the Landsat 5, 7, 8, and 9 surface reflectance satellite images available in Climate Engine. EVI time series were also extracted and used to compare with NDVI. These indices were extracted from a small polygon around each site in order to reduce noise. This study evaluated data from January 1st, 2015 to December 31st, 2017.

The equation for NDVI is as follows,

$$NDVI = \frac{NIR - R}{NIR + R} \quad (\text{Equation 1})$$

where NIR and R are the reflectances of the NIR band (750–850 nm) and the Red band (680 nm), respectively.

The equation for NDWI is as follows,

$$NDWI = \frac{NIR - SWIR}{NIR + SWIR} \quad (\text{Equation 2})$$

where NIR and SWIR are the reflectances of the NIR band (750–850 nm) and the SWIR1 band (1.55–1.75 μm), respectively.

2.3 Data Processing

The NDVI, EVI, and NDWI time series obtained from Climate Engine were downloaded as comma-separated value (csv) files and replotted using Google Sheets. The pre-disturbance NDVI and NDWI values from around January to August of 2015 were averaged and used as the baseline. This baseline is sometimes referred to as the pre-disturbance mean value. In order to understand the differential effects of El Niño on various types of forests, as illustrated in Figure 2, the Disturbance Magnitude (DM) from the baseline and the Recovery Time (RT) from the lowest point to a level consistently close to baseline were estimated from the NDVI and NDWI time series data.

3. Results

The PDSI drought index measures the average soil moisture conditions, with positive and negative values representing wet and dry conditions, respectively. A PDSI value between -0.5 and 0.5 represents normal soil moisture conditions, while PDSI > 4 represents very wet conditions, and PDSI < -4 represents an extreme drought (Climate Citation Internet Team, 2005). As shown in Figure 3A, from 2015 to 2016, the PDSI values for the study region were < -2 for about 13 months, with four months staying below -4. The annual PPT was lower for 2015 (~1700 mm) compared to other years between 2010 to 2018 (~1900 to 2000 mm), with very low monthly PPT from August to December 2015 (4–43 mm/month) (Figure 3B). The CWD, another measure of dry season intensity, was high in the study region during the time period (Figure 3C).

Figure 4 shows the NDVI and NDWI time series for the 4 IF sites in the Tapajós National Forest. A drop in NDVI value from a pre-disturbance mean value of ~ 0.8 to below 0.6 was consistently observed around Nov-Dec, 2015. The NDVI values recovered to >0.6 within 1 month. For IF2 and IF4 plots, the NDVI returned to the previous mean value within 1 month. For IF1 and IF3, it fluctuated for a few months before consistently returning to the pre-disturbance mean values. The NDWI values were generally close to the pre-disturbance mean values, with only a transient minor decrease for IF2.

Figure 5 shows the NDVI and NDWI time series for 4 sites of FL. The NDVI values consistently dropped from ~ 0.8 to below 0.6 around Nov-Dec, 2015. It first returned to >0.6 in about a month but fluctuated before consistently returning to the previous mean values. For FL1 and FL3, the NDVI fluctuated for 4 to 6 months, while the NDVI of FL2 and FL4 fluctuated for ~ 18 months. The NDWI values for FL1, FL2, and FL4 had a substantial negative deviation from the pre-disturbance mean values. Specifically, the NDWI value of FL2 and FL4 began deviating around December 2015, bottoming in June-July of 2016, and returning close to the baseline around 18 months later (although never fully recovering). The NDWI value for FL1 began deviating around September 2015, bottoming in January 2016, and returning to the baseline in September 2016. The NDWI value for FL3 generally remained close to the pre-disturbance mean values.

Figure 6 shows the NDVI and NDWI time series for 4 sites with forest gain. A drop in NDVI value from ~ 0.8 to below 0.6 was generally observed around Nov-Dec, 2015. The NDVI values generally recovered to >0.6 within a month. For FG1 and FG3, the NDVI returned to previous mean values in about 6 months. For FG2, the NDVI returned to previous mean values in about 3 months. For FG4, the NDVI values first returned to previous mean values after 6 months, but seemed to have more fluctuation compared to other sites of FG. The NDWI values deviated from the mean values and generally bottomed in December 2015, excluding FG2. The NDWI of FG1 and FG4 began deviating around September to December 2015, returning close to the pre-disturbance mean value in July. Compared to FG1 and FG4, FG2 and FG3 returned close to the baseline relatively faster.

4. Discussion

The time series drought index PDST, monthly PPT, and CWD (Figure 3) clearly illustrate that during the 2015-2016 El Niño, the chosen study region had an extended period of extreme drought.

In this study, we used NDVI as the primary index to monitor vegetation greenness and photosynthesis capacity. The NDVI time series was also compared to EVI (data shown in Appendix 1), another commonly used vegetation greenness index. In general, both indices showed similar trends. However, on a few occasions when the NDVI data exhibited a major drop, the EVI data showed a positive spike, which exceeded the normal EVI range of -1 to 1 and are likely artifacts (EOS Data Analytics, 2022). Along with major drops in NDVI values starting from around November to December 2015, we also generally observed drops in NDWI. The NDWI reductions sometimes occurred earlier and often were more pronounced compared to the corresponding NDVI values, suggesting NDWI is more sensitive to dry conditions in the study region. We hypothesized that this is likely because the loss of chlorophyll and leaves from trees is relatively a slower process compared to water loss during drought. The observation seems to corroborate with other studies (Joiner et al., 2018).

Our NDVI results show that the greenness of IF sites in the Tapajós National Forest generally returned to the pre-disturbance mean values faster compared to the areas of FG or FL. The consistent nature of the NDWI results indicates that the overall water content of the IF sites were barely affected by the drought. These observations are likely because the highly developed ecosystems in intact forests confer their stability and resilience against perturbations. For example, the diverse and fully functioning units of the ecosystems, consisting of both drought-tolerant and drought-sensitive trees, allow forests to maintain their soil moisture (Thompson et al., 2009). In times of drought, drought-tolerant trees that rely on a deeper water supply are able to hold onto their greenness for the longest period of time, protecting the moisture in the topsoil that other drought-sensitive plants rely on (Haberstroh & Werner, 2022). Areas of FG and FL, on the other hand, often have decreased biodiversity and altered ecosystems. Moreover, significant deforestation reduces overall evapotranspiration and disrupts the

natural water cycle in the rainforests, likely leading to less rainfall and ultimately increased drought within the microclimates. Even modest deforestation could affect local precipitation patterns and likely cause the remaining forest to experience a significant change in water and light availability. The effects can be manifested by vegetation index changes.

The results from this study cannot conclusively establish the general difference between areas of FG and FL. Although our results seem to suggest that the sites of FG tend to have faster recovery rates compared to most sites of FL, there is an exception. The NDVI and NDWI time series of FL3 show patterns similar to that in intact forests. The inconsistencies may be explained by the heterogeneous nature of areas with FL or FG. The sites of FL and FG could vary significantly in terms of types and ages of trees, biodiversity, level of deforestation, and other conditions. We were unable to obtain these detailed characteristics of each chosen site. As such, it is unclear which factors are affecting the results. Furthermore, since only 4 sites of each were selected in this study, our results may not represent areas of FG/FL as a whole.

During the 2015-2016 El Niño, although areas of FL and FG generally showed a higher negative deviation of vegetation indices relative to IFs, some studied areas (e.g. FL3 and FG4) seemed to be relatively resilient. The results suggest that it is feasible to improve forest health by carefully managing the level of deforestation and/or establishing healthy ecosystems via reforestation.

This study is limited to assessing the short-term changes of rainforests in the study region based on vegetation greenness and water content, which are often used to evaluate the health of the forests. NDVI and NDWI cannot accurately assess the long-term resilience of rainforests as they can not assess parameters such as vegetation structure and variation in tree stem thickness (Boulton et al., 2022). Additionally, NDVI has been shown to saturate in dense vegetation cover (Huete et al., 1997). However, since clear decreases were consistently observed in our data, we believe our data was within the dynamic range and thus, this limitation should not affect our analysis. Furthermore, other studies (Boulton et al., 2022) have used the Vegetation Optical Depth (VOD) index, a microwave-derived product with a wider

dynamic range, to assess forest resilience (Moesinger et al., 2020). We did not have the capacity to compare our data with the VOD index in order to understand the long-term resilience of the selected sites. During the data mining process, we also noticed gaps between data points likely due to cloud cover, which, in a few cases, made it difficult to determine exactly when the NDVI or NDWI results returned to the pre-disturbance mean.

To our knowledge, this is the first time the combination of NDVI and NDWI has been used to assess forest health and stress in the Lower Tapajós region. This study also takes advantage of the diverse statuses of the forests in the region and conducts an in-depth assessment of the difference between IFs, areas of FG, and areas of FL. In the future, other remote sensing techniques such as Sun Induced chlorophyll fluorescence (SIF) can also be used to track canopy photosynthesis and assess forest health (Hernández-Clemente et al., 2017). In addition, a combination of field-work and satellite data could provide information on the characteristics of each site and mechanistically pinpoint specific factors affecting the health of forests.

Conclusion

This study investigated short-term forest health by monitoring the changes of NDVI and NDWI in the Lower Tapajós region, Brazil, after the 2015-2016 El Niño. After comparing the short-term resilience of NDVI and NDWI in IFs, areas of FG and FL, we observed that the IFs are significantly less vulnerable to drought based on smaller disturbance magnitudes and faster recovery rates. Although a general distinction between areas of FG and FG was unable to be made, our data suggests that carefully managing reforestation efforts and levels of deforestation can improve forest health. Ultimately, the superior conditions of IFs affirm the necessity of preserving the Amazon to maintain its resilience. Doing so would not only maintain the livelihood of the Amazon, but would also benefit the world on a much larger scale by repressing global climate change.

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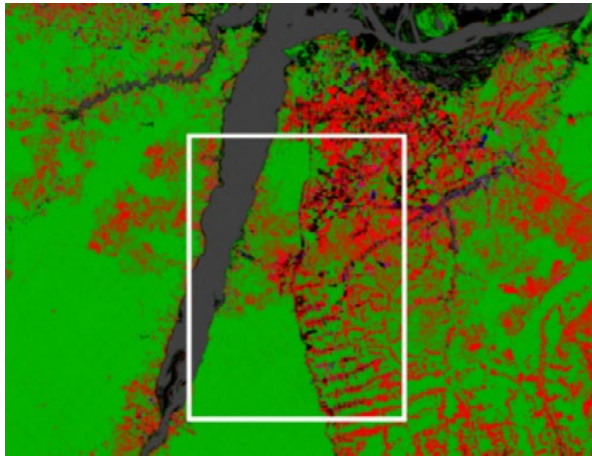
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Figure 1. Study Region and Study Sites

A: Study Region within the Lower Tapajós. Green = Intact Forest; Red = Forest Loss; Blue = Forest Gain



B: 12 chosen sites of study. Green = Intact Forest; Blue = Area of Forest Gain; Red = Area of Forest Loss.

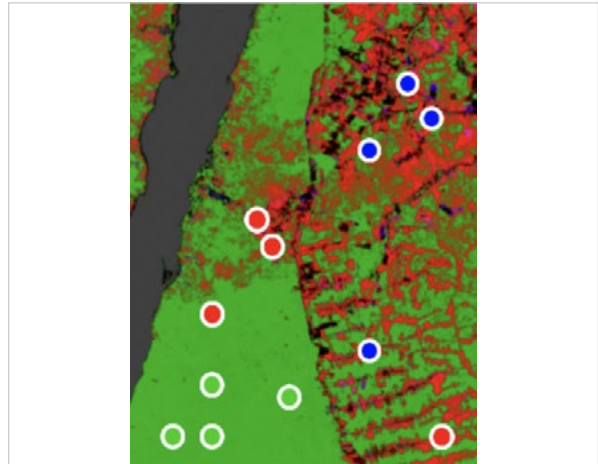


Figure 2. Schematic Representation of Effects of Climate Disturbance on NDVI and NDWI. RT = Recovery Time; DM = Disturbance Magnitude; Red Line = Pre-disturbance Mean.

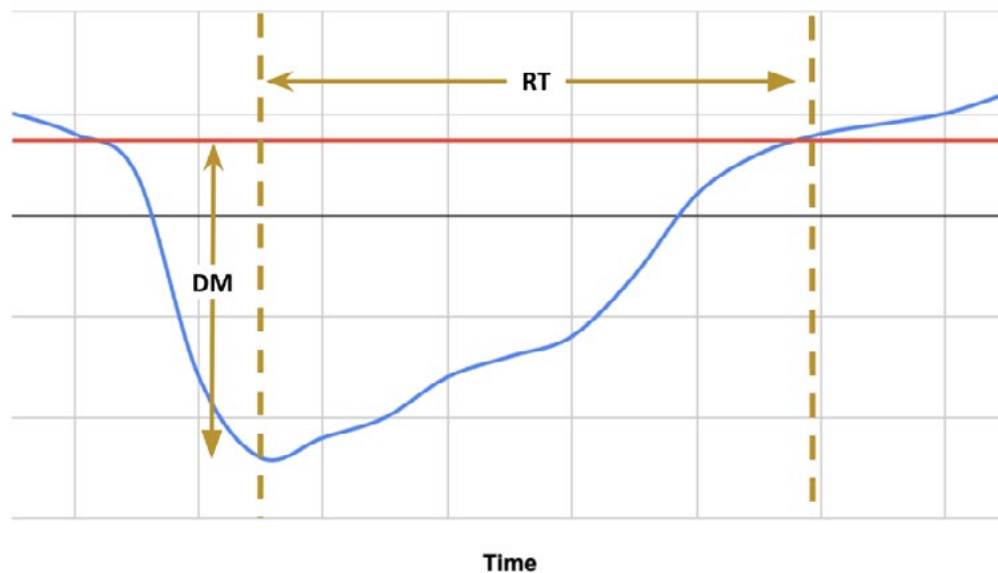


Figure 3. Time Series of the Three Environmental Indices (PDST, PPT, and CWD) Analyzed in the Study Region from January 2010 to December 2018

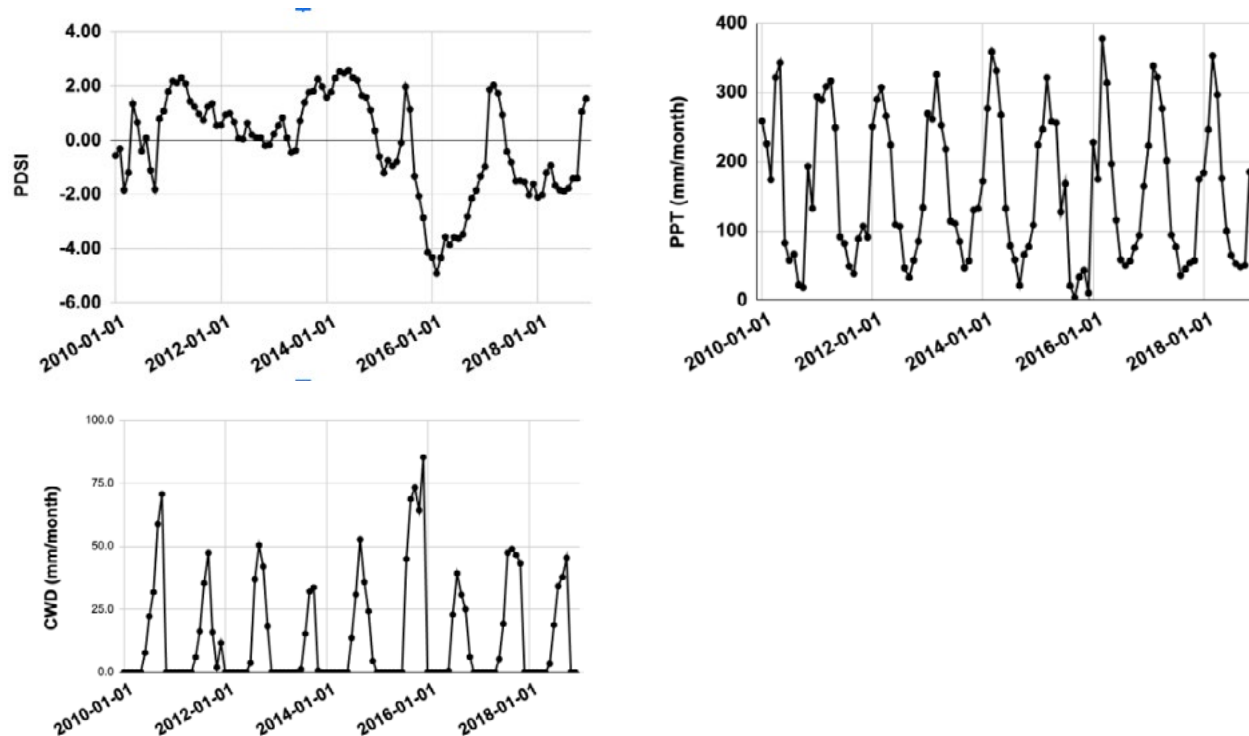


Figure 4. NDVI and NDWI for the Intact Forests in the National Forest Area. Green (NDVI); blue (NDWI); dash lines represent pre-disturbance mean values.

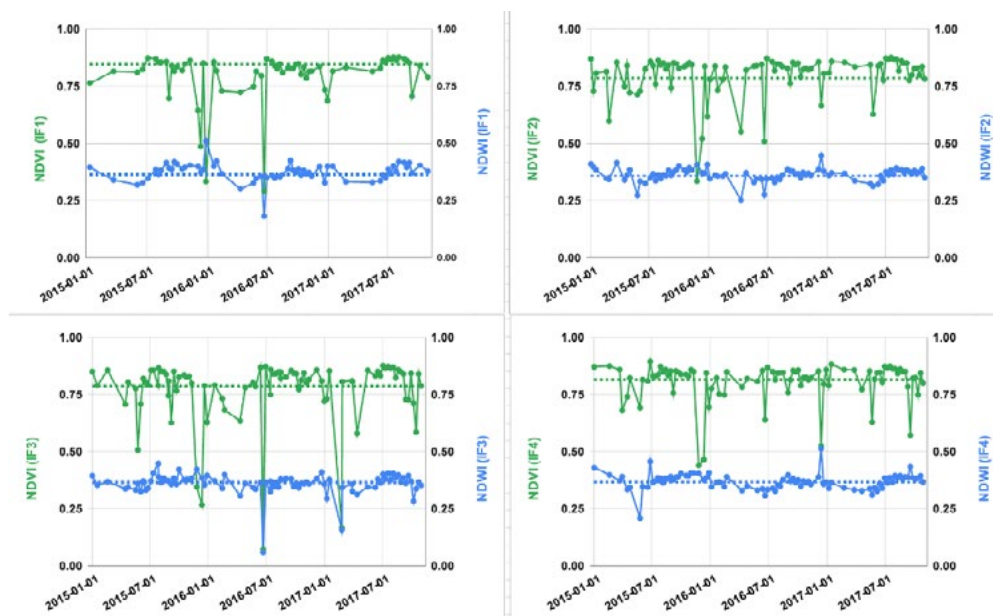


Figure 5. NDVI and NDWI for Areas with Forest Loss. Green (NDVI); blue (NDWI); dash lines represent pre-disturbance mean values.

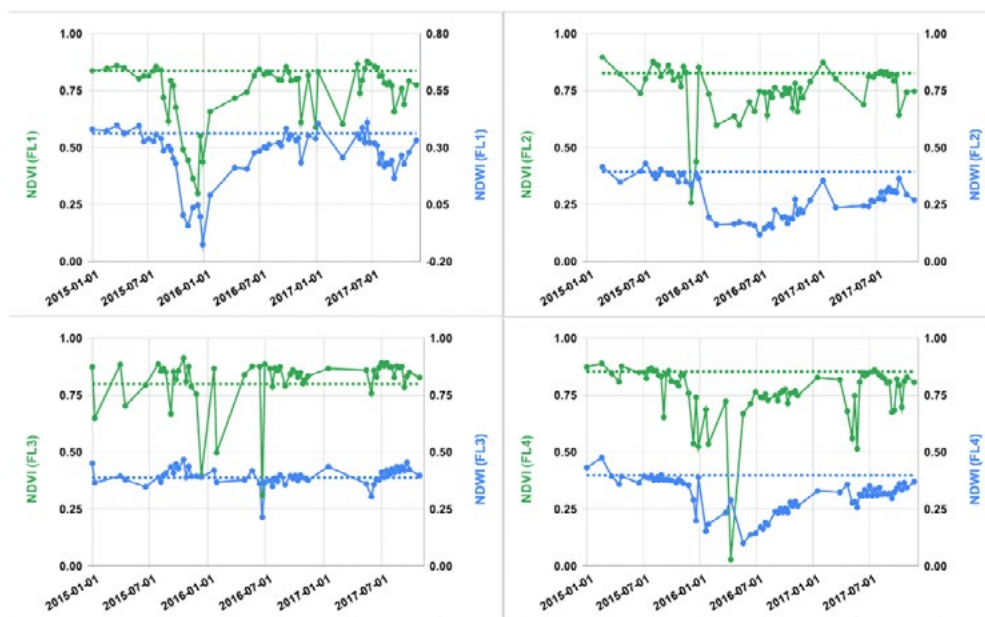
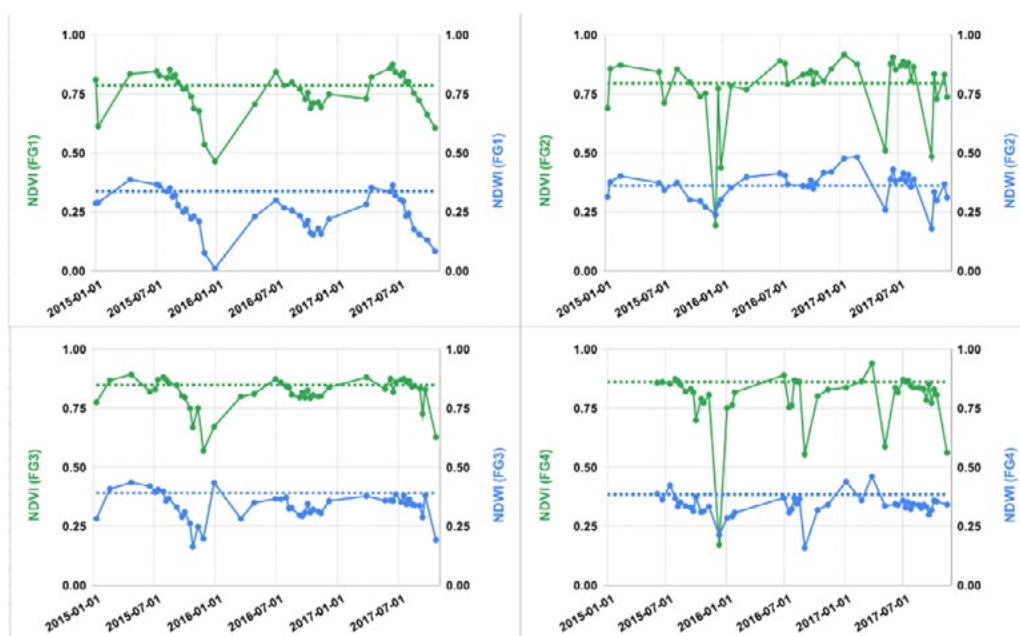
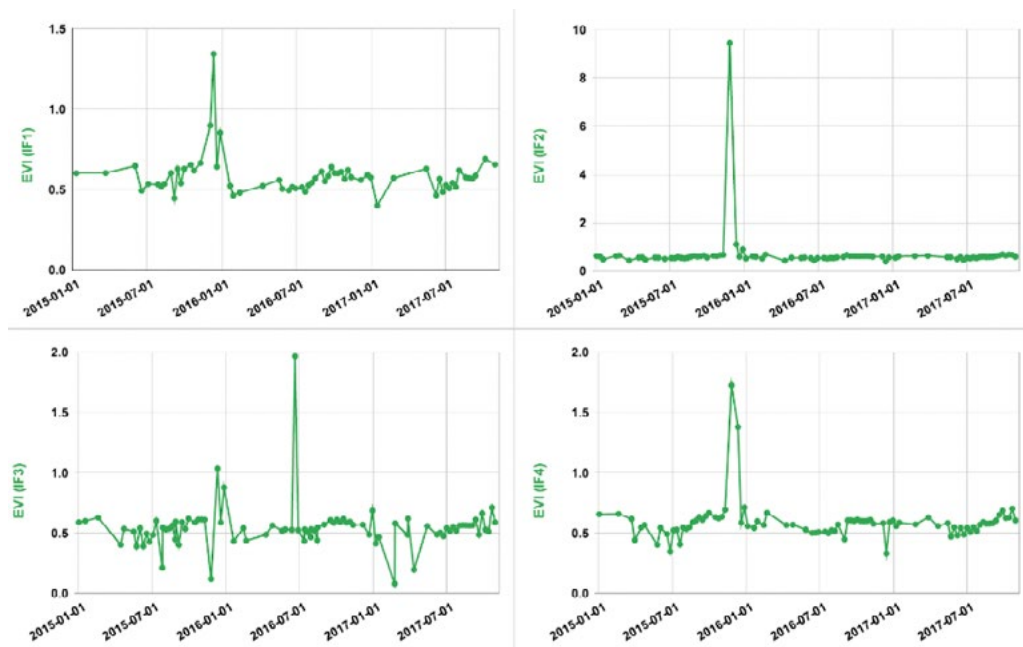


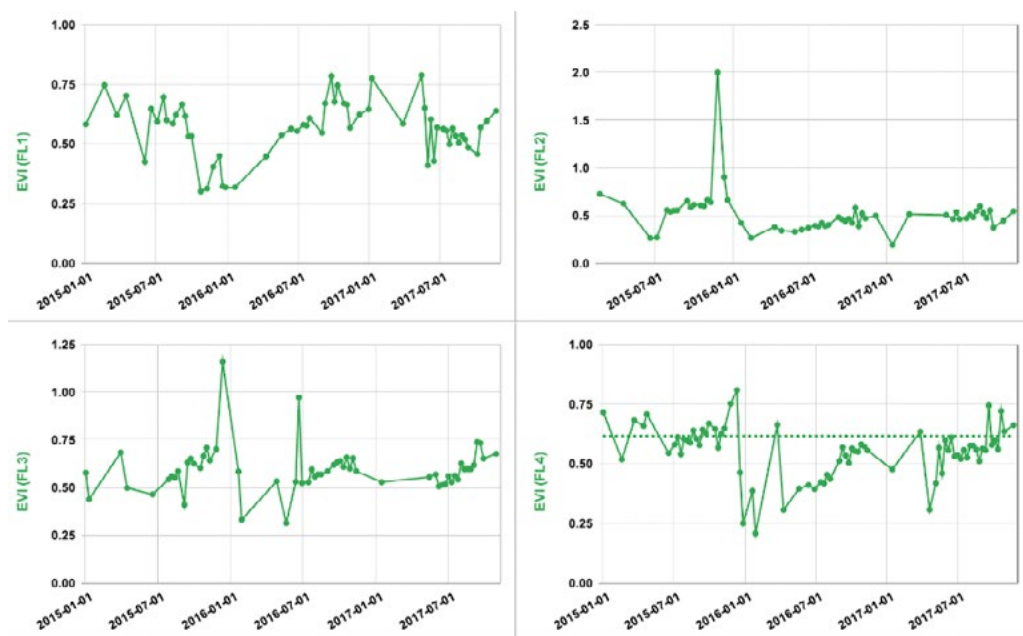
Figure 6. NDVI and NDWI for Areas with Forest Gain. Green (NDVI); blue (NDWI); dash lines represent pre-disturbance mean values.



Appendix 1. EVI Time Series for the Intact Forests in the National Forest Area



Appendix 2. EVI Time Series for Areas with Forest Loss



Appendix 3. EVI Time Series for Areas with Forest Gain

