

# Efficacy of Monitoring Management Activities in Longleaf Pine in North Carolina Using Remote Sensing

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## Abstract

Using remote sensing as a tool to monitor forest management intervention may reduce the time and funds needed to actively visit landscapes. However, previous research typically studied the effects of large-scale disturbances, such as wildfires, to demonstrate the efficacy of using vegetation indices to track forest change. To better understand the limitations of these indices, Landsat 8 NDVI and NBRT values were calculated for 99 management units consisting of longleaf pine stands under stewardship of The Nature Conservancy of North Carolina. These units were across nine preserves held by TNC, in the Coastal Plain region of North Carolina. To assess change, indices values before and after management activity were compared, as well as indices values in management units with and without management intervention. These values were significant, but the changes were minimal. Linear mixed models were created to test the explanatory power that time since treatment, seasonality, treatment size, basal area, treatment type, and preserve locality had on the change in NDVI or NBRT. While these variables failed to explain the changes in indices values post-intervention, a variety of other factors may potentially express the reduction in NDVI or NBRT: other vegetative growth, climate variability, and the scale of the data may influence these indices' results. As such, while the mixed models did not find these management characteristics explanatory, that alone does not reject the thesis that remote sensing may be useful for monitoring fine-scale change. Further study and extended data collection may prove useful.

## Introduction

### *The Longleaf Pine Landscape*

Longleaf pine (*Pinus palustris*) forests depend on fire. The pine's success begets the success of a long list of flora and fauna that rely on the longleaf pine ecosystem, a poster child for ecosystem-based management. In the typical longleaf pine savannah, the vast overstory of longleaf pine provides breeding habitat for a multitude of birds; most notably, the endangered red-cockaded woodpecker (*Dryobates borealis*). A keystone species, the red-cockaded woodpecker excavates holes into decayed bark for nests and roosts, which are later used by other cavity-nesting species. Lower on the forest floor, the ground cover of grasses and flowering plants provide cover for small mammals, amphibians, and reptiles – helpful for hiding from larger predators. Equally as useful are the gopher tortoises' (*Gopherus polyphemus*) burrows and tunnels, which allow other species to hide and travel. These pines provide habitat for over 300 wildlife species, of which 29 are endangered (Shelton, 2012). With its historic range significantly reduced – about 2.2% of longleaf pine's original extent remains today (Jose et al. 2007) – conservation and preservation of these longleaf pine ecosystems are of utmost importance; they provide ecological significance, increased biodiversity, and recreational opportunities in an increasingly rare habitat.

Conservation planning and management of longleaf ecosystems rely on active management, such as prescribed burns, thinning through vertical structures, and removal of competitive species. In the southeastern United States, land managers use prescribed burns to remove brush and litter that choke out young longleaf pines, reduce competition from competitive hardwood species, and control brown-spot needle blight (Boyer et al. 1983). These prescribed burns promote longleaf pine health and success, whilst also supporting the much-reduced longleaf pine ecosystem. Thinning in the mid- and overstory reduces competition from young hardwoods and decaying or dead trees that reduce sun exposure on the forest floor.

### *Change Detection and Recovery Monitoring*

Past research has examined the use of vegetation indices to monitor landscape changes after disturbances. Typically, these disturbances consist of large-scale wildfires that can change the forests' structure. These high intensity fires have the vegetative impact that may be detected by vegetation indices, such as Normalized Difference Vegetation Index (NDVI) and Normalized Burn Ratio Thermal (NBRT) (see below). While these indices have been utilized to monitor large-scale disturbances, such as wildfires or agricultural activity, fine-scale disturbances such as prescribed burning or thinning are less studied. For example, NDVI has successfully been used to monitor vegetative changes in a variety of landscapes, such as tallgrass prairie and mesas and canyons (Mohler et al. 2009, Leon et al. 2012). Landsat-derived NBRT has been utilized to delineate wildfire boundaries and severity (Holden et al. 2005). While vegetation clearly shifts after a hot and intense wildfire, less intense prescribed burns may not display a similar decline in NDVI and NBRT. The vegetation reduced by prescribed burns may be less than that of wildfires, and the decrease due to prescriptions may slight. These large-scale disturbances may be more distinguishable versus the potentially softer influence that prescribed burns and forest thinning may have.

Vegetative growth may also differ post-disturbance. With increasing fire severity, vegetation communities are shifted towards an early-successional state that can be dominated by a suite of grasses, forbs, and broadleaf species, versus the original forest structure pre-fire (Ireland and Petropoulos, 2015). In the southeastern and western United States, historic fire suppression has increased fuel loading that sparks large and intense wildfires. Intense fires may burn vegetative areas and strongly influence recovery and species succession (Stephens et al. 2015, Assal et al. 2018). Unfortunately, vegetation indices do not inherently consider the type of new growth post-disturbance. Additionally, while our study does not examine the nativity of the undergrowth, new growth post-management may differ based on species pre-existing on the landscape, and their ecological usefulness should be assessed.

### **Objectives**

The Nature Conservancy of North Carolina manages many tracts of longleaf pine ecosystems in the southeastern regions of the state. They would like to examine the

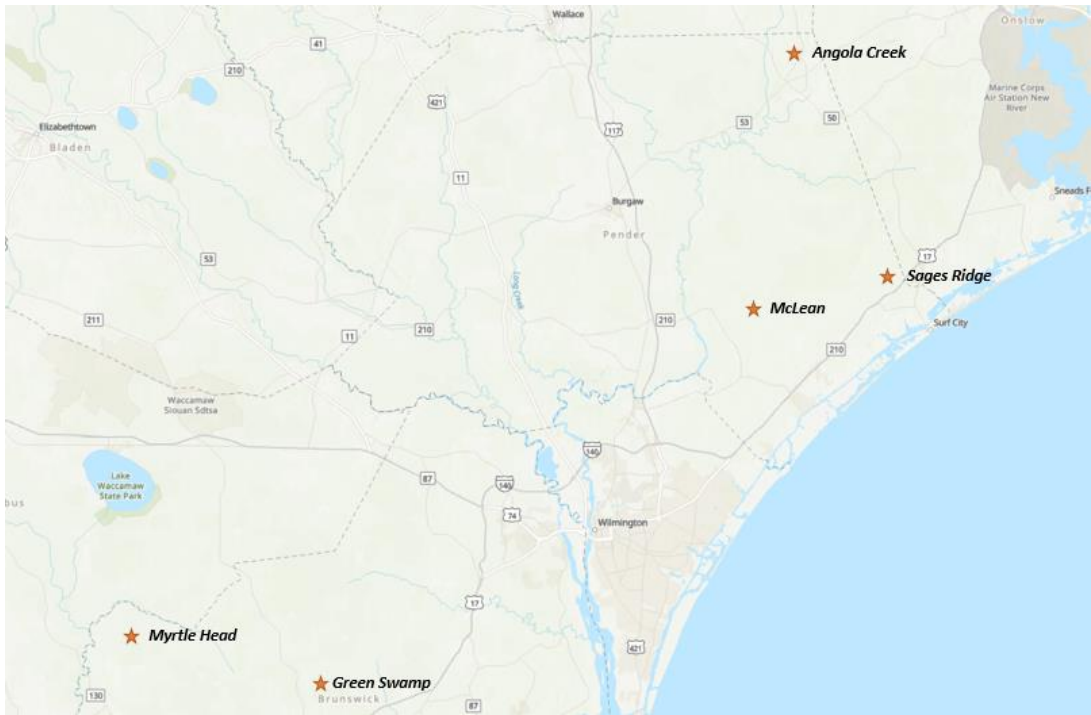
potential uses of remote sensing to monitor longleaf pine stands that are actively managed for wildlife and other ecosystem services. Utilizing remote imagery may be more efficient and less costly to the organization, particularly since the longleaf pine stands are relatively widely distributed throughout the region. My objective in this project was to assess the feasibility of using freely available, remotely sensed data products to do this assessment. Specifically, my objectives were:

- Examine the significance of changes in vegetation indices before and after management intervention
- Examine the significance of changes in vegetation indices between management units with intervention and management units without intervention
- Determine if time since management and next captured satellite image, seasonality, management size, basal area, management type, and preserve explain the change and variation in the data

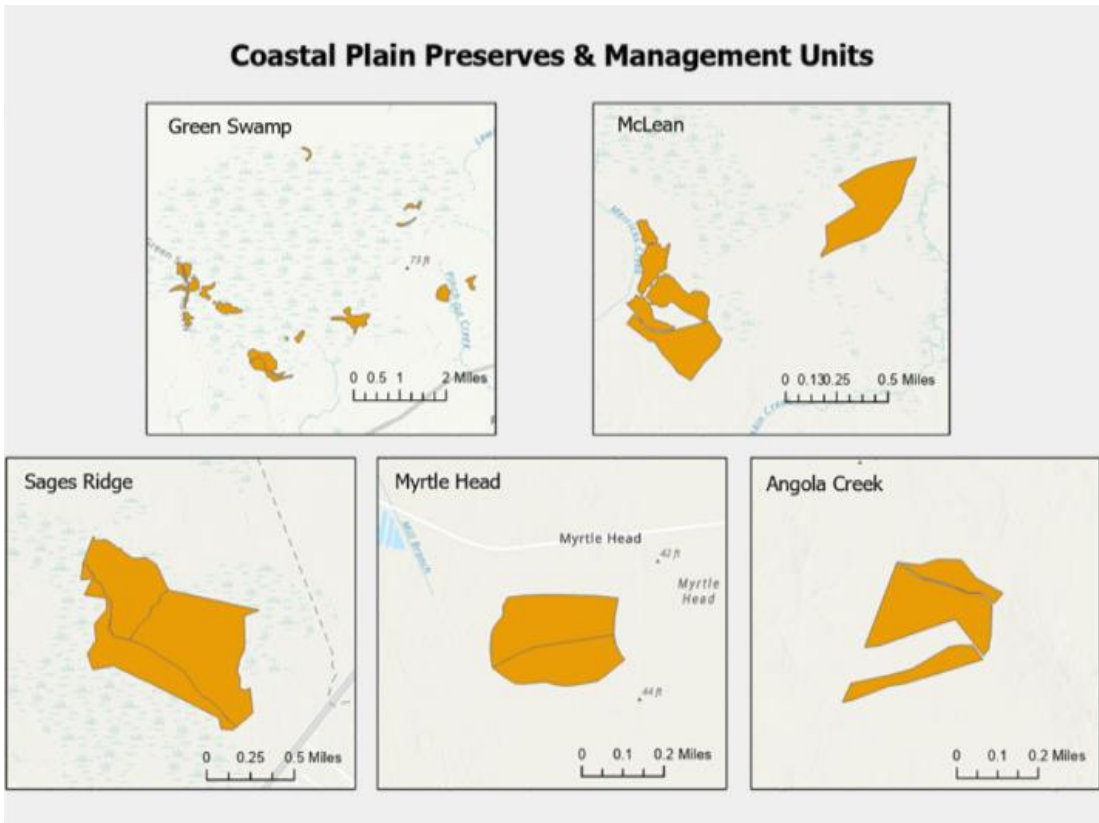
## **Methods**

### *Study Area*

This study was based in nine preserves owned by The Nature Conservancy across North Carolina's Coastal Plain and Sandhills regions. These preserves have actively managed longleaf pine stands, which will henceforth be called, "management units." Five preserves were based in the Coastal Plain, with 27 management units across the five preserves (Figures 1, 2). Four preserves were based in the Sandhill region, with 25 management units across the four preserves (Figure 3). Only management units that were actively managed, whether they were thinned or prescribed burned, were considered in our analyses.

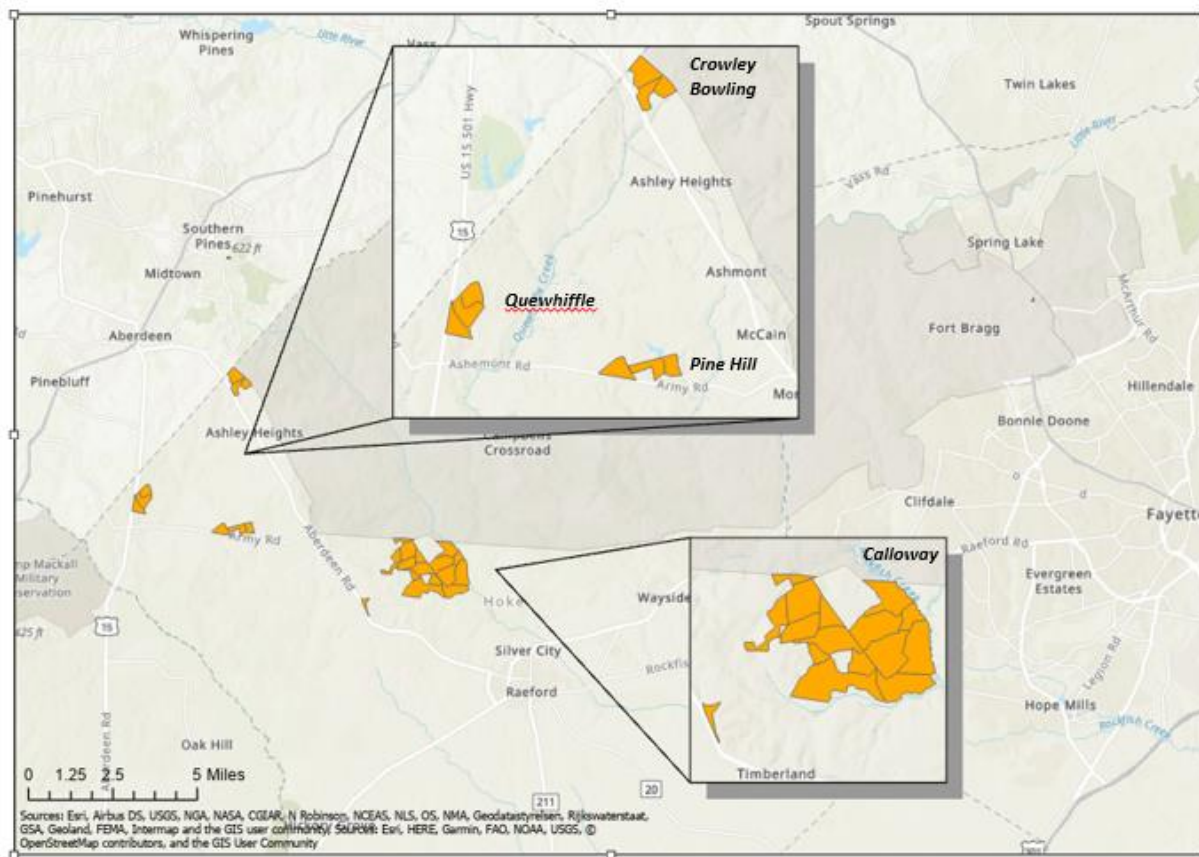


**Figure 1.** The five focal TNC preserves in the Coastal Plain.



**Figure 2.** Preserves in the Coastal Plain and their associated management units.

## Sandhill Preserves and Management Units



**Figure 3.** The four preserves in the Sandhill region and their associated management units.

### *Satellite Imagery and Vegetation Indices*

National Agriculture Imagery Program (NAIP) was originally explored as the primary source of analysis for natural resource monitoring, since NAIP imagery is free, has 1-meter resolution, and is flown every other year, the imagery may capture large changes in the landscape. However, utilization of the imagery assumes the ability to view changes visually within the image. As these management activities have more fine-scale impacts (versus wildfires or natural disasters), changes are more granular and difficult to visualize. Additionally, NAIP imagery was determined unfit because of its images are taken at different times each capture year. Its lack of anniversary-dated information also feeds into a lack of control during capture: each photograph may be taken at a different angle and cannot be calibrated across years. As such, utilizing NAIP was deemed unfit due to the images' greater variation across time, and I turned to Landsat 8 as a better fit for the objective of the project.

The Landsat 8 satellite was launched in 2013, capturing data on a 16-day cycle circling earth. Data is captured on a 30m scale. The regularly scheduled capture dates allow us

to compare pre- and post-management intervention, potentially capturing differences in vegetation through satellite imagery. Additionally, Landsat satellites capture images in nadir (directly above) the surface of the earth, reducing errors that may occur while comparing images with angular differences. Landsat 8 comprises 11 bands; in this instance, I focused on the following bands: Band 4 Red, Band 5 Near Infrared, Band 6 & 7 Shortwave Infrared, and Band 10 & 11 Thermal Infrared.

Google Earth Engine (GEE) (Gorelick et al. 2017) was used to decrease downloading and processing time needed to access data. USGS Landsat 8 Surface Reflectance Tier 1 data from GEE was atmospherically corrected, and cloud cover was masked prior to the calculation of NDVI. The Landsat 8 Collection 1 Tier 1 8-Day NBRT composites were developed from top-of-atmosphere (TOA) reflectance, from which NBRT was developed. The NBRT composites were provided by Google. Data was clipped to the study area, and vegetation indices (NDVI and NBRT) were created using the aforementioned bands.

#### *Normalized Difference Vegetation Index*

NDVI is intended to capture green leaf area, as a function of red absorption and near infrared reflectance (Glenn et al. 2008). Values range from -1.0 to 1.0, in which sparse vegetation is recognized as approximately 0.2 to 0.5, and dense vegetation as 0.6 to 0.9 (Fu and Burgher, 2015). It is computed as:

$$\text{NDVI} = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red}) \quad (1)$$

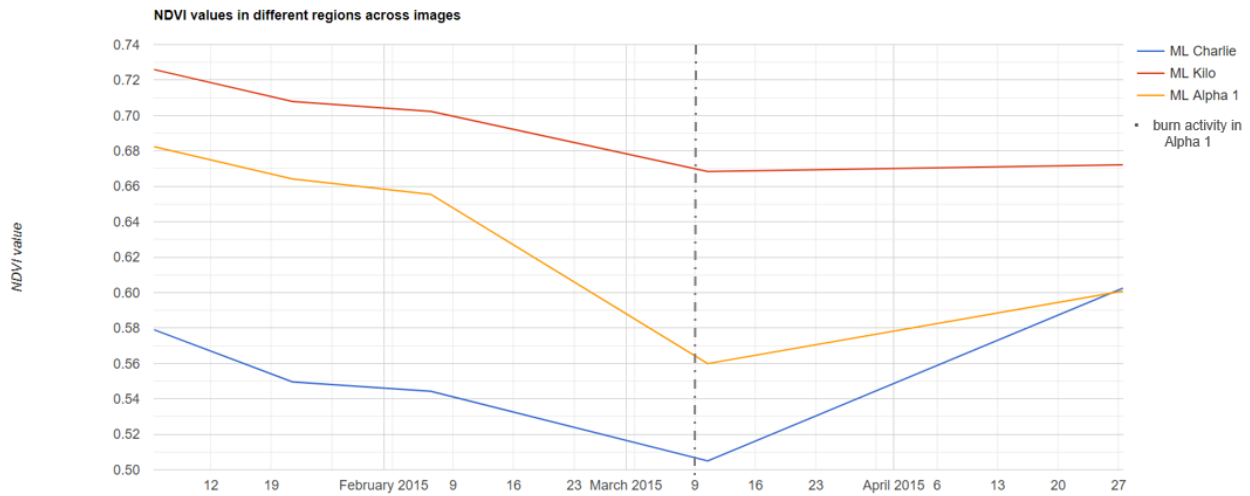
#### *Normalized Burn Ratio Thermal*

NBRT determines if a burn has occurred or not, as well as the intensity of the burn. The NBRT spectral index was chosen for its two-band combination that employs both SWIR and TIR bands. The TIR bands help distinguish between burned and non-burned areas (Holden et al. 2005, Trigg and Flasse, 2001). Values range from -1.0 to 1.0, in which lower NBRT values signify more intense burns. NBRT is calculated as follows:

$$\text{NBRT} = (\text{NIR} - \text{SWIR}(\text{Thermal}/1000)) / (\text{NIR} + \text{SWIR}(\text{Thermal}/1000)) \quad (2)$$

Both indices are used as a measure of vegetation: NDVI as a measure of green-leaf vegetation, and NBRT as a measure of burn existence and severity. GEE allows us to quickly examine and compare changes in NDVI or NBRT over time, particularly as time series charts throughout the years and before and after management interventions.





**Figure 4.** Example of an NDVI time series pre- and post-management intervention. A prescribed burn was performed at the Alpha 1 management unit in the McLean Preserve during the dormant season.

NDVI and NBRT pixel values were averaged over each management unit. Data was downloaded from GEE from 2013 to 2018. Indices values before and after each management activity was taken to determine potential significance.

NDVI differencing takes the difference between the NDVI values of two dates. The objective is to potentially detect change between the two dates (Lyon et al. 1998).

*NDVI Differencing (dNDVI)*

$$dNDVI = NDVI_{pre} - NDVI_{post} \quad (3)$$

Similarly, NBRT takes the difference between the NBRT value of two dates, typically to find the potential of burned and severity of burned areas. Positive dNBRT values depict more severe burns.

*NBRT Differencing (dNBRT)*

$$dNBRT = NBRT_{pre} - NBRT_{post} \quad (4)$$

To examine if the changes in vegetation indices was due to the actual management activity, I took the difference between the pre- and post-management NDVI and NBRT. We compared the vegetation index difference in the unit with activity with the difference of an adjacent or nearby stand without activity; our hypothesis being that if the two stands were significantly different, then the significance may be due to the management activity. The paired unit without activity had to be adjacent or nearby with a similar basal area.

### Management Characteristics

Six variables were considered to explain the variation in differencing between our vegetation indices (Table 1).

**Table 1.** Response variables and independent variables used to explain variation in differences in vegetation indices.

<i>Response Variables</i>	<i>Independent Variables/Effects</i>	<i>Type of Effect</i>	<i>Units</i>
dNDVI	Time Since Management	Fixed	Days
dNBRT	Season	Fixed	Spring, Summer, Fall, Winter
-	Treatment Size	Fixed	Acres
-	Basal Area	Fixed	≤10, 11-39, 40-70, 71-90, ≥90
-	Treatment Type	Fixed	Growing Season RX Fire, Dormant Season RX Fire, LLP Plantation 2nd Thinning, Midstory Reduction-Aerial Release, Midstory Reduction-Mechanical, Midstory Reduction-Spot Spraying, Overstory LLP Thinning, Reduced Competition for Young LLP, Timber Stand Improvement
-	Preserve	Random	Angola Creek, Calloway, Crowley Bowling, Green Swamp, McLean, Myrtle Head, Pine Hill, Quewhiffle, Sages Ridge

#### *i. Time Since Management*

I took the time difference between the date the management activity was performed and the date that the next satellite image that was available. Because some available images were taken nearly a month after the management activity and others were taken the day after a management activity, this introduced some variability within our data. Data with a longer interval between the activity and the next available satellite image may have less detectable changes in vegetation indices, as there is more time for regeneration or other factors to influence the landscape (Holden et al. 2005).

ii. *Season*

Because most management activities were performed in the winter or summer, there may be some variability in the indices differencing. Based on the date that the management activity was performed, I introduced season into my potential explanatory variables.

iii. *Treatment Size*

Because some treatment sizes were extremely small (one acre), while others were large (over 100 acres), there may be some potential differences in our NDVI and NBRT that may influence our ability to detect vegetative change. A smaller treatment size may not be easily detectable, while a larger treatment size may be better able to be detected.

iv. *Basal Area*

Basal area (BA) is the average amount of area occupied by tree stems per unit of area (in this case, square feet per acre). BA was based on categorical data collected by TNC in 2015. Five categories were noted: less than 10 BA, 11-39 BA, 40-70 BA, 71 to 90 BA and over 90 BA (Table 2).

**Table 2.** Number of management units within each basal area category.

<i>Basal Area Category</i>	<i>Number of Management Units</i>
≤10	34
11-39	40
40-70	16
71-90	6
≥90	3

Basal area was used as a proxy for canopy openness. Greater basal area assumed less penetration through the forest canopy, potentially reducing the satellite's ability to detect understory regeneration and removal through intervention. Passive detectors, such as Landsat 8, do not penetrate through thick forest canopy to the forest floor (Latifi et al., 2016). As such, vegetation differences due to management activities may be less able to be detected in stands with greater basal area. Most of our units had less than 70 BA.

v. *Treatment Type*

Treatment type references the management activity conducted by the Nature Conservancy. In the Coastal Plain, this was mainly prescribed burns during the dormant and growing season (Table 3). In the Sandhills, this was mainly mid-story thinning (mechanical/aerial) and over-story thinning (Table 4). Longleaf pine planting, spot-spraying, and timber stand improvement interventions were also occasionally noted, but were not management activities that were performed often throughout our 2013-2018 time range.

**Table 3.** Example of the data utilized for the Angola Creek Preserve and its associated management units and management activities.

ANGOLA CREEK UNITS			
Management Unit	Treatment Date	Treatment Type	Treatment Size (acres)
AC Buccaneer	3/10/2014	Dormant Season RX Fire (ac)	5
AC Buccaneer	2/1/2015	Dormant Season RX Fire (ac)	60
AC Buccaneer	2/22/2018	Dormant Season RX Fire (ac)	60
AC Anvil	6/1/2015	Growing Season RX Fire (ac)	140
AC Anvil	2/23/2018	Dormant Season RX Fire (ac)	140
AC Bobwhite	2/28/2014	Dormant Season RX Fire (ac)	65
AC Bobwhite	5/26/2016	Growing Season RX Fire (ac)	65
AC Bobwhite	2/21/2018	Dormant Season RX Fire (ac)	65

**Table 4.** Number of management activities per treatment type.

<i>Treatment Type</i>	<i>Number of Activities per Treatment Type</i>
Dormant Season RX Fire	41
Mid-story Reduction-Mechanical	21
Growing Season RX Fire	17
Overstory LLP Thinning	8
LLP Plantation 2 <sup>nd</sup> Thinning	4
Mid-story Reduction-Aerial Release	3
Reduced Competition for Young LLP	2
Timber Stand Improvement	1
LLP Planted	1
Mid-story Reduction-Spot Spraying	1

Based on the type of treatment, some treatments may be more detectable versus others. For instance, because prescribed burns generally reduce the duff layer and remove young understory vegetation, they may be less detectable than mid-story or over-story thinning, which actively removes larger trees in the stand.

*vi. Preserve*

Preserve was considered a random effect variable in our analysis. Because the nine preserves were scattered across North Carolina, the locality of the preserve may influence the changes in vegetation. As such, we may consider the amount of variation in our data that is potentially attributable to the preserve.

### *Statistical Analyses*

All statistical analyses were performed within R, version 3.6.1 (R Core Team, 2019). Graphs were created under R package, 'ggplot2', (Wickham, 2016), and linear mixed models performed with 'lme4' (Bates et al. 2014). Analyses for NDVI considered all management activities (n = 99), while NBRT only considered prescribed burns (n = 58).

#### *Before and After Management Activity*

To examine the significance of NDVI and NBRT values before and after management activity, I performed a paired t-test or non-normal equivalent per vegetation index.

#### *Paired Management Units*

To examine the potential significance of NDVI and NBRT differencing values in management units with activity and adjacent units without activity, I performed a paired t-test or non-normal equivalent per vegetation index.

#### *Linear Mixed Models*

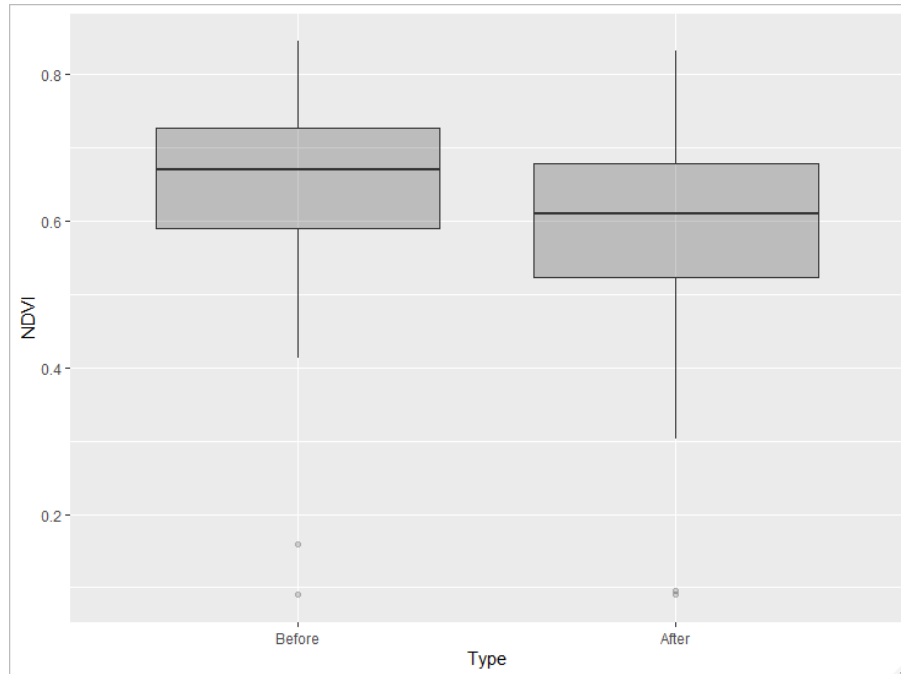
To determine if the management characteristics of each management activity could explain the variance within our data, I assessed the relationship between the six characteristics and the change in each vegetation index. For example, I created a linear mixed model (Bates et al. 2014) with the change in NDVI as the response variable, and time since management, season, treatment size, basal area, treatment type as fixed effects, and preserve as a random effect. This linear mixed model was repeated with the change in NBRT as the response variable.

For each of these models, I assessed the assumptions of normality and homoscedasticity using the 'hist' and 'plot' functions (R Core Team, 2019). Data for before and after comparisons was determined normal, and no transformations were performed. Data for paired management unit comparisons was determined non-normal, and non-parametric t-tests were performed to bypass its irregularity. To find the most parsimonious model, the full model with all six variables was reduced and compared for suitability using the Akaike Information Criterion (AIC) (Sakamoto et al. 1986).

## **Results**

### *NDVI: Before and After Management Activity*

NDVI values before and after management intervention were compared across 99 management units in the Coastal Plain and Sandhills. On average, NDVI prior to activity was 0.65 (SD = 0.117), and NDVI post-activity was 0.59 (SD = 0.129). The average dNDVI (0.0573) accounted for about 9% decrease (0.0573/0.65) in NDVI post-management.

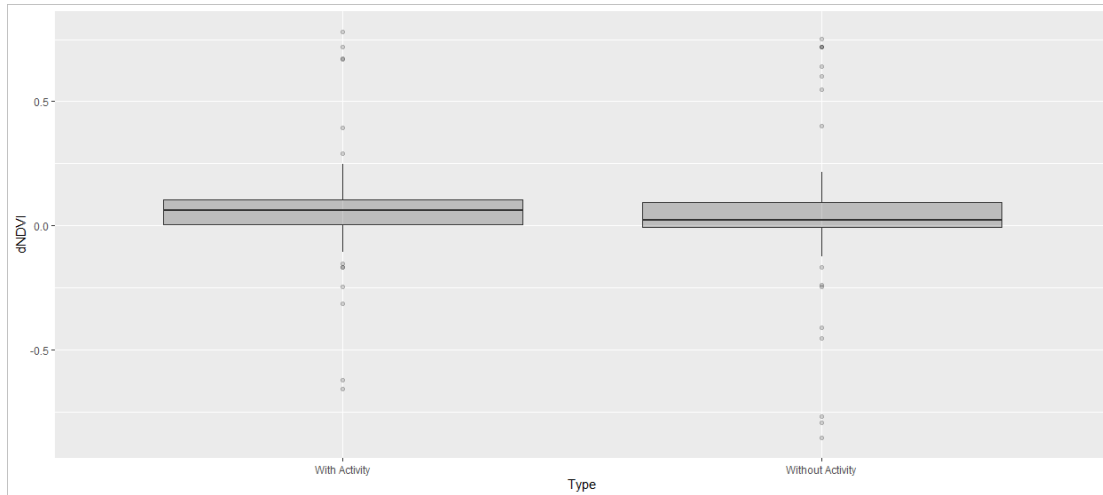


**Figure 5.** Box-plot comparison between NDVI values before a management activity and after a management activity (n = 99). Solid lines are medians, and shaded boxes are interquartile ranges.

Because NDVI values before and after management activity were normal (Appendix), a paired t-test was performed to test the significance between the mean NDVI values before and after activity ( $P < 0.0001$ ). The mean values before and after activity were significantly different.

#### *NDVI: Paired Management Units Comparison*

NDVI differencing values were compared across 194 management units (97 units with management activity, and 97 without) in the Coastal Plain and Sandhills. Two units from the original 99 were removed from this analysis, as adjacent units had undergone the same management activity and were unable to be compared. On average, an activity decreased NDVI by 0.065 (SD = 0.2), while units without activity during the time period decreased NDVI by 0.041 (SD = 0.25). The difference of these means is 0.0236; units with management intervention had an average dNDVI higher than that of units without. As a percentage, dNDVI in stands without management was 36.3% less than that of the stands that were managed ( $1 - 0.04/0.65$ ).



**Figure 6.** Box-plot comparison of NDVI differencing in management units with management activity versus management units without activity. Solid lines are medians, and shaded boxes are interquartile ranges.

Because dNDVI for both units with management activity and units without activity were not normal (Appendix), a Wilcoxon signed-rank test was performed to test the difference in the median between the two ( $p = 0.006164$ ). The median values between units with and without management activity are significantly different.

#### *NDVI: Linear Mixed Models*

To find the most parsimonious model, a base model with dNDVI as the dependent variable, preserve as a random effect, and five other factors as the fixed effects (Table 1) was created. An explanatory variable was removed in each iteration of the mixed model, until the model with the lowest AIC score was found (Table 5). In this case, none of the independent variables were found significant.

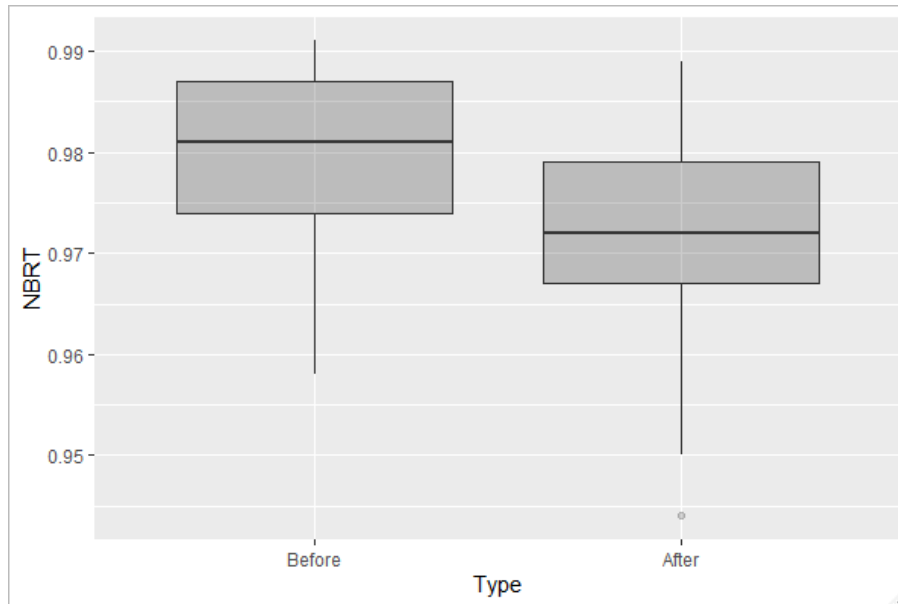
**Table 5.** Linear mixed models created and compared for NDVI, and their associated AIC values.

<i>Model</i>	<i>Variable Removed</i>	<i>AIC</i>
Model 0	-	-54.023
Model 1	Time Since Management	-69.004
Model 2	Season	-85.506
Model 3	Treatment Size	-102.156
Model 4	Basal Area	-124.799

The final model (Model 4), with only treatment type as an explanatory variable, was found insignificant.

### *NBRT: Before and After Management Activity*

NBRT values before and after intervention activity were compared across 58 management units and found normal. The average NBRT value prior to management activity was 0.9787 (SD = 0.0094), while the average NBRT value post-management activity was 0.9721 (SD = 0.0087). The difference of these averages (0.0065) showed a ~0.7% decrease in NBRT post-management.



**Figure 7.** Box-plot comparison for NBRT values before and after management activity (n = 58). Solid lines are medians, and shaded boxes are interquartile ranges.

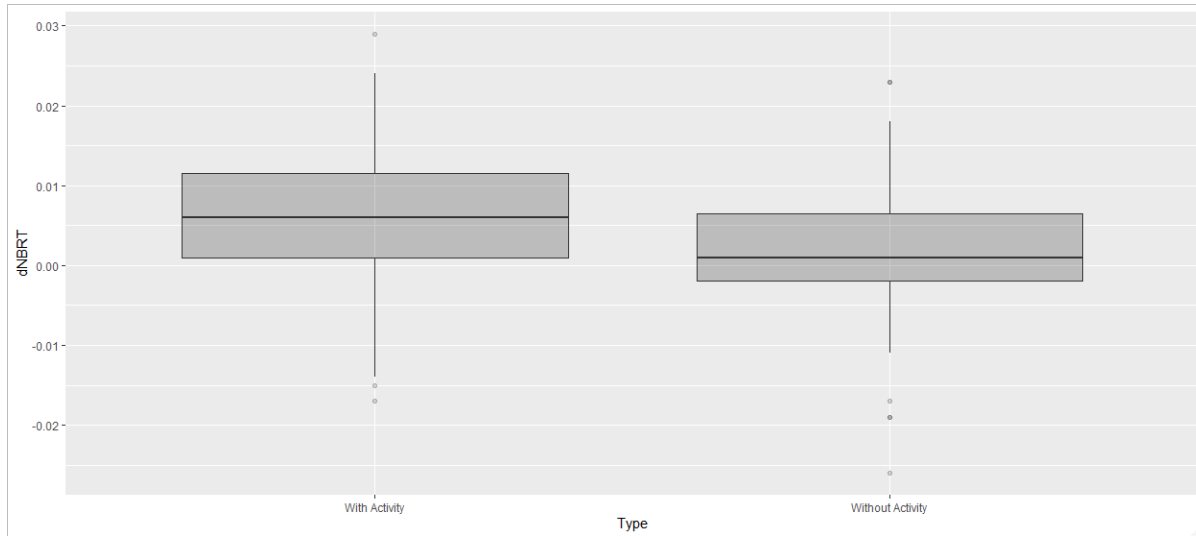
The average NBRT values pre- and post-management intervention was significantly different ( $p < 0.0001$ ).

### *NBRT: Paired Management Units Comparison*

NBRT differencing values were compared across 112 management units (56 units with management activity, and 56 units without activity during the same time period). Two units were removed from this analysis, as adjacent units had undergone the same activity at the same time. Because the data was not normal, a Wilcoxon signed-rank test was performed. On average, NBRT values reduced by 0.0056 (SD = 0.01) in management units with intervention activity. On the other hand, NBRT values reduced by 0.0015 (SD = 0.01) in management units without intervention activity. The difference of these means is 0.0041; as units that were burned had a higher difference in NBRT than units that were not burned. As a percentage, units that were not burned were 76.3% lower in dNBRT than those units that were prescribed burned. A paired t-test



verified the significant difference between the means for units with and without intervention activity ( $p = 0.0048$ ).



**Figure 8.** Box-plot comparison of NBRT differencing values in management units with management activity versus management units without activity. Solid lines are medians, and shaded boxes are interquartile ranges.

#### *NBRT: Linear Mixed Models*

To find the most parsimonious model, a base model with dNBRT as our dependent variable, preserve as a random effect, and five other factors as our fixed effects (Figure 2) was created. An explanatory variable was removed in each iteration of the mixed model, until the model with the lowest AIC score was found (Table 6).

**Table 6.** Linear mixed models created for NBRT and their associated AIC values.

<i>Model</i>	<i>Variable Removed</i>	<i>AIC</i>
Model 0	-	-249.832
Model 1	Season	-268.894
Model 2	Basal Area	-311.746
Model 3	Time Since Burn	-329.134
Model 4	Treatment Size Acres	-349.178

In this case, each iteration proved unfruitful, and none of the explanatory variables were found significant. Our final model, with only treatment type as an explanatory variable, was insignificant.

### **Discussion**

The comparisons in NDVI and NBRT pre- and post-management intervention were significant, as well as the comparisons in management units with intervention and adjacent units without intervention. Indeed, all percentage changes in the four

comparisons displayed a decrease in NDVI or NBRT post-management and comparatively with units without intervention. However, this significance may be explained by the relatively large sample sizes ( $n = 99/97$  and  $n = 58/56$ ). While these differences were significant, they were slight. Because of the larger sample sizes, the averages and medians in our paired t-tests and non-parametric equivalents may always prove significantly different from one another. Despite this, the percentage change in indices values in paired comparisons proved a greater reduction in NDVI and NBRT post-treatment. In units without management, conditions were potentially more stable and as such, mitigated the reduction in our vegetation indices.

Because of the significant differences in the comparisons and overall decreases, I sought to explain the variance in the data with seasonality, basal area, time between management activity and the next satellite image captured, treatment size, treatment type, and the preserve locality. If the differences in NDVI or NBRT were notable because of management intervention, they could potentially be explained by these management characteristics.

However, these mixed models exploring change in NDVI and NBRT were insignificant, and the explanatory variables were not explanatory in terms of the change in vegetation indices. This may be due to the scale of our data: because the average of NDVI and NBRT was taken across the management unit, the indices values are representative of the whole area, whereas the pixel values of the unit may differ. Similarly, some management activities were only a portion of the stand, and as such would only affect a portion of our data that may be averaged out. Because these are fine-scale interventions, the changes in vegetation may be less able to be captured when examining average values. In this case, as Landsat 8 has a 30m by 30m resolution, it may be useful to utilize a different satellite that captures multispectral images on a finer scale (e.g. Planet satellites - 3m, Rapideye - 5m, Sentinel 2 - 10m). Planet and Rapideye are collected every day, although they are on a pay-per basis (Planet Team, 2017). Sentinel-2 is collected every five day (ESA, 2015) and is free to the public.

While the percentage change in NDVI and NBRT post-treatment could not be explained by the selected management characteristics, they may be explained by other factors. The reduction in vegetation during the management intervention may be lost in the noise of natural vegetative growth, particularly in the spring and summer seasons. As NDVI is a measure of greenness, the growth of other vegetation may displace the reduction post-treatment. The heavy-handedness of the treatment may also play a role. In the instance of prescribed burns, severity of the fire and regularity of the prescription influences the vegetated reduction on the ground (Escuin et al. 2007). Additionally, regrowth on the ground may depend on the species available in the seed bank. The data comparison included regions across North Carolina, assuming similar history and growth patterns. However, this is not necessarily the case, and more information may be needed to better understand the understory growth on the ground. For instance, non-native species establishment versus native species establishment may differ in growth post-

disturbance (Nelson et al. 2008). Furthermore, climate impacts and variation may be better accounted for by considering the year at which management is performed. Total precipitation, average temperature, and other weather variables may have an impact on vegetative growth. As such, a variety of factors, such as species establishment, climate, competitive interactions, and other factors may explain the variance within the data.

## **Conclusions**

While previous literature focuses on the impact of large-scale disturbances on vegetation indices, fine-scale management interventions are less studied. Changes in NDVI and NBRT were slight but significant, although these differences could not be explained by the management characteristics considered in this study. These findings may be due to other factors, such as severity of the prescribed burn and the objective basal area for a thinning. Therefore, future management should note an estimation of duff layer and understory removed in a burn, as well as the thinning prescription. Such estimations may better explain the variation in NDVI and NBRT values.

Moving forward, data collection on the ground may be improved by incorporating vegetation removal estimates from burns and thinning prescriptions. They may also be improved by noting the plants in the area; as non-native and native species may differ in vegetative return. If midstory removal is mainly for hardwood control and release of longleaf pine, such species may be noted. Reduction on the ground may be related to the changes in vegetation indices, and the relationship may be utilized to design a general range of fine-scale impact that I found in the hundredths and thousandths place.

In terms of remote sensing, while the changes in indices were significant but unexplained, there may be other methods TNC could approach. For instance, if funding allowed, such data may be utilized for hyperspectral imagery to recognize spectral signatures of desired and undesired plant species (Underwood et al. 2003). Other sources of finer-resolution data may be utilized, as previously mentioned. Finer-resolution data may produce more accurate averages of NDVI and NBRT that may be better compared. Finally, while comparison across years using NAIP imagery may not be useful, classifying satellite images to compare pre- and post-management may prove worthy. Further exploration and research may better determine further resourcefulness of remote sensing and satellite systems.

## **Acknowledgements**

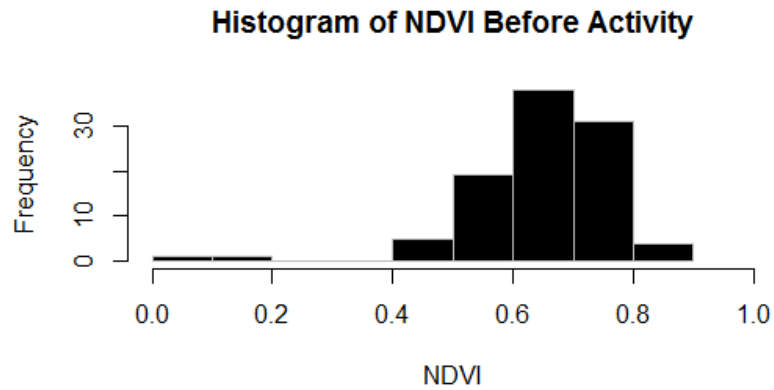
This project is based on the background knowledge and data provided by the Nature Conservancy of North Carolina, for without which, this project would not be possible. I am deeply grateful to my advisor, Dean Urban, for his continued patience, as well as to Jennifer Swenson, John Poulsen, and Ram Oren for their serial guidance and emotional support. Finally, I could not have come this far without the grounding love of my family, friends, and partner – I am so thankful for all the encouragement and laughter they shared with me.

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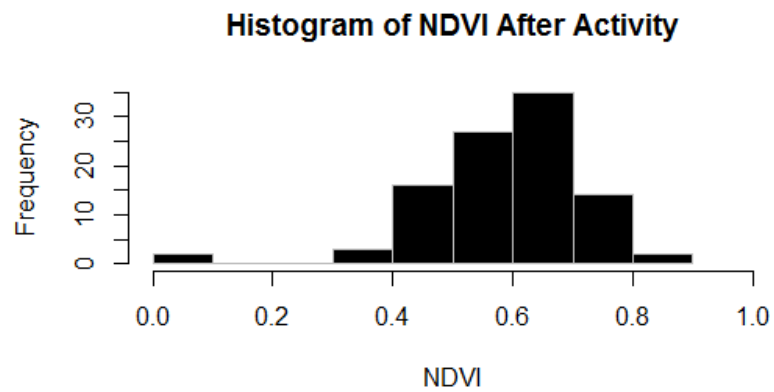
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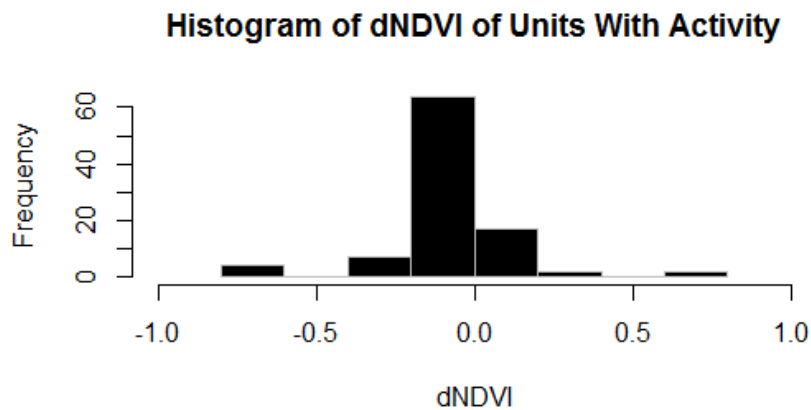
## Appendix A: Tests of Normality



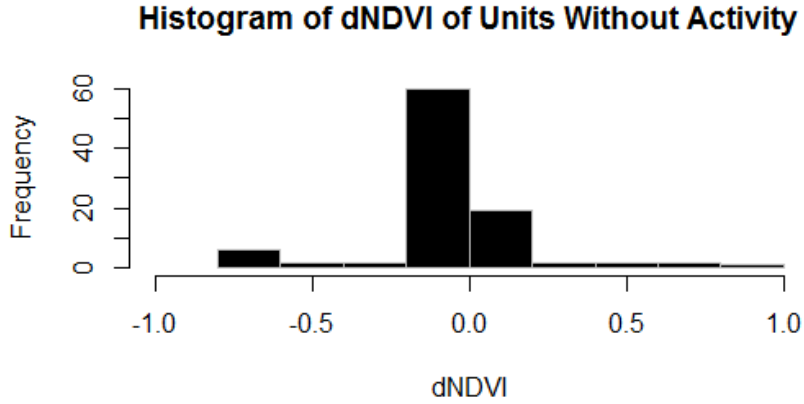
**Figure A1.** Histogram to preview normality for NDVI values in management units prior to management intervention.



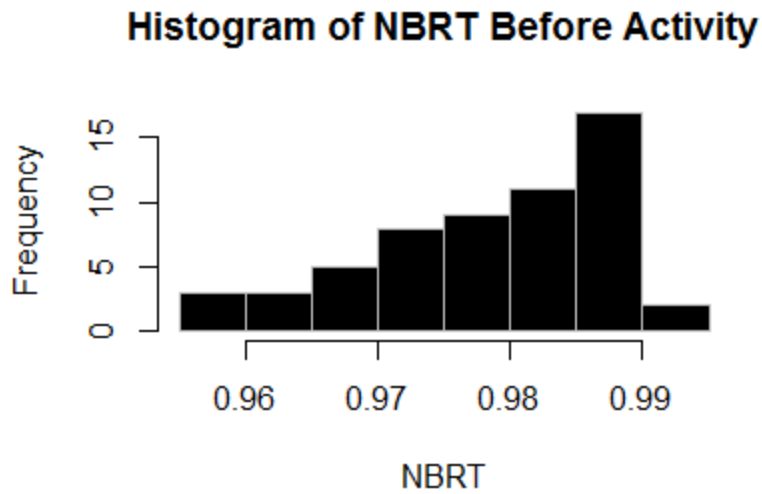
**Figure A2.** Histogram to preview normality for NDVI values in management units after management intervention.



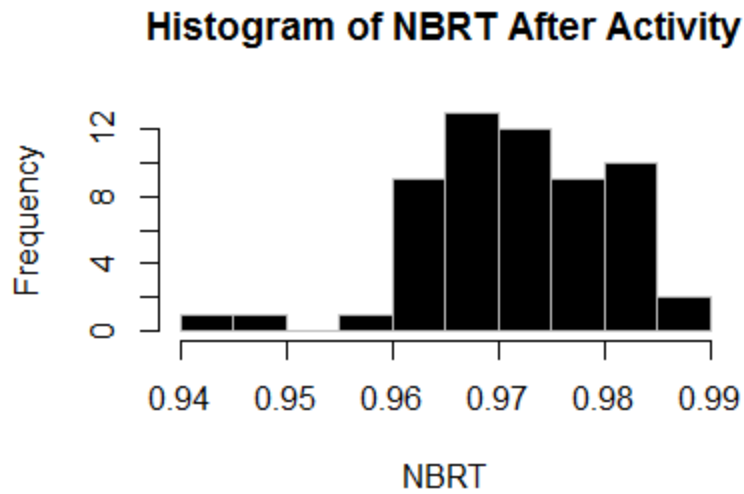
**Figure A3.** Histogram to preview normality for NDVI differencing values in management units with intervention. The NDVI value pre-management activity was subtracted from the NDVI value post-management activity.



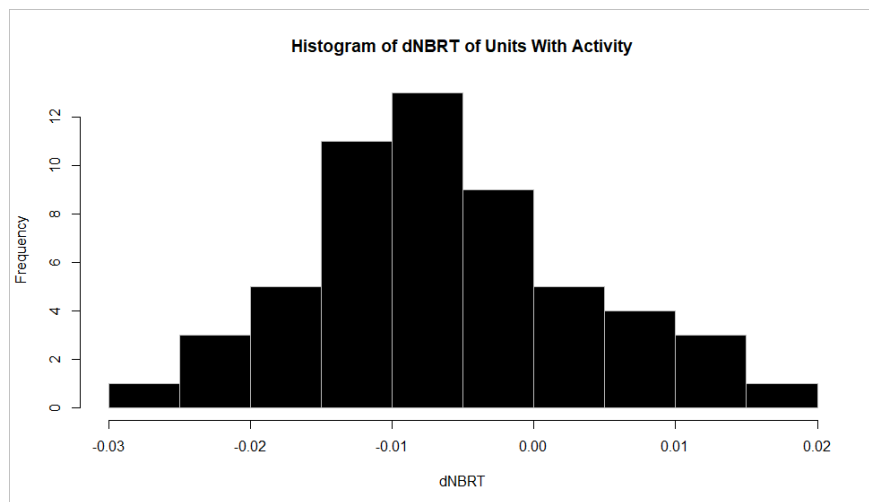
**Figure A4.** Histogram to preview normality for NDVI differencing values in management units without intervention in the same time range as the unit with intervention. The NDVI value pre-management activity was subtracted from the NDVI value post-management activity. These “paired” units were either adjacent or nearby stands with similar basal area category.



**Figure A5.** Histogram to preview normality for NBRT values in management units prior to management intervention.

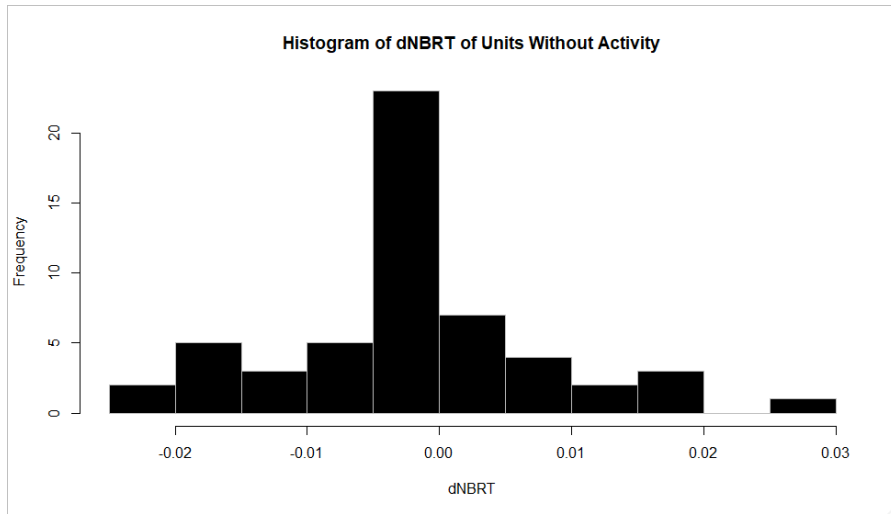


**Figure A6.** Histogram to preview normality for NBRT values in management units after management intervention.



**Figure A7.** Histogram to preview normality for NBRT differencing values in management units with intervention. The NBRT value pre-management activity was subtracted from the NBRT value post-management activity.





**Figure A8.** Histogram to preview normality for NBRT differencing values in management units without intervention in the same time range as the unit with intervention. The NBRT value pre-management activity was subtracted from the NBRT value post-management activity. These “paired” units were either adjacent or nearby stands with similar basal area category.