TIME SERIES ANALYSIS OF VEGETATION DYNAMICS AND BURN SCAR MAPPING AT SMOKY HILL AIR NATIONAL GUARD RANGE, KANSAS USING MODERATE RESOLUTION SATELLITE IMAGERY

by

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Abstract

Military installations are important assets for the proper training of armed forces. To ensure the continued viability of training lands, management practices need to be implemented to sustain the necessary environmental conditions for safe and effective training. For this study two analyses were done, a contemporary burn history and a time series analysis. The study area is Smoky Hill Air National Guard Range (ANGR), an Impact Area (within the range) and a non-military Comparison Site. Landsat 5 TM / 7 ETM+ imagery was used to create an 11 year composite burn history image. NDVI values were derived from MODIS imagery for the time series analysis using the statistical package BFAST. Results from both studies were combined to make conclusions about training impacts at Smoky Hill ANGR and determine if BFAST is a viable environmental management tool. Based on this study the training within Smoky Hill ANGR does not seem to be having a negative effect on the overall vegetation condition. It was also discovered that BFAST was able to accurately detect known vegetation disturbances. BFAST is a viable environmental management tool if the limitations are understood.

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Chapter 1 - Introduction

Sustainable use of military training lands is necessary for long-term provision of realistic and safe conditions that support maneuvers and exercises. The Department of Defense (DoD) controls 7,859,618 hectares (ha) of land within the United States (Gorte *et al*., 2012). Training activities on these land holdings can have dramatic impacts on the environment (Shaw *et al*., 1989). The land owned by the DoD generally has little urban development and contains areas of large unbroken natural landscapes. Some installations are larger than most U.S. national parks (Cohn 1996).

In compliance with DoD policy, an Integrated Natural Resource Management Plan (INRMP) was implemented at Smoky Hill Air National Guard Range (ANGR) (Engineering-Environmental Management, Inc. 2007). Installation-specific INRMP guides ecosystem management within military mission requirements and, at Smoky Hill ANGR, also governs livestock and agricultural leases (Busby *et al.*, 2007). The goals for natural resource management at Smoky Hill ANGR are "to enhance and maintain biological diversity within the Range boundaries, while assuring the successful accomplishment of the military mission. Management practices should minimize habitat fragmentation and promote the natural pattern and connectivity of habitats; protect rare and ecologically important species; maintain and mimic natural processes; and restore species, communities, and ecosystems (Busby *et al*., 2007, p. 7)".

In 2002, Smoky Hill ANGR asked the Kansas Biological Survey (KBS) to do conduct an inventory of the flora and fauna for their training lands and to rate the overall ecological condition at the range (Busby *et al*., 2007). The KBS concluded that Smoky Hill ANGR is an example of a large preserved tallgrass prairie with large spans of unbroken prairie that serves as a hotspot for biodiversity for the Great Plains. Overall, KBS categorized the grassland communities as "good" because of their thoughtful management practices . A goal for the INRMP is to raise the overall quality from "good" to "excellent" (Busby *et al*., 2007).

All of the surveys and analyses performed by KBS at Smoky Hill ANGR were extremely time intensive, requiring the collection of immense amounts of data about the range to document baseline conditions and inform the ongoing management of the tallgrass prairie. A tool that could be included within future INRMP at Smoky Hill ANGR to complement the KBS vegetation survey, is a time series analysis of vegetation conditions for the entire range. While Smoky Hill ANGR land managers have information concerning what grass species are present at the range, they do not currently have access to data describing long-term vegetation trends or quantifying the magnitude and extent of disturbances over the entire range.

Research Question and Objectives

This study uses a combination of traditional supervised satellite image classification and time series temporal decomposition methods to estimate and compare vegetation dynamics for a military and non-military site in Smoky Hills ecoregion of Kansas. Specific questions that will be answered are:

- What is the frequency and spatial distribution of significant disturbances in the vegetation trend at Smoky Hill ANGR and do these differ significantly from adjacent non-military lands?
- What is the long-term interannual trend in vegetation conditions, as inferred using normalized difference vegetation index (NDVI) data, at Smoky Hill Air National Guard Range (ANGR) and do estimated trends differ significantly from adjacent non-military lands?

- Does the frequency and spatial distribution of abrupt intraannual changes detected in the long-term trend component of the temporal decomposition (using moderate resolution satellite imagery) agree with classified images of burn scars (using high spatial resolution satellite imagery) for the same time period?

The comparison of long-term trends and abrupt changes between the military and non-military site will be used to evaluate whether the training activities and land management practices in place at Smoky Hill ANGR manifest as different vegetation responses. The results here will be combined with that from other military installations to determine whether vegetation dynamics are consistently different on training lands versus surrounding non-military landscapes.

To answer the questions above, the following objectives will be accomplished:

- Collect Landsat 5 TM, Landsat 7 ETM+, and MODIS MOD13Q1 16-day NDVI composite images for the period 2001-2011.
- Apply a minimum distance supervised classification on the red and near-infrared bands of monthly Landsat imagery to identify burn scars (disturbances) and create a data product reflecting the minimum number of annual burns for 2001-2011.
- Use the Breaks For Additive Seasonal and Trend (BFAST) temporal decomposition method, within the statistical software program “R”, to extract the long-term interannual trend, number of abrupt changes (breaks) in the linear trend, and magnitude and direction of breaks from a 2001-2011 time series of MOD13Q1 images.
- Use a Student’s t-test to evaluate the significance of long-term intraannual trends, perform a Chi-square contingency table analysis to detect important differences in the number of breaks in trend between study sites, and run a logistic regression to

determine whether BFAST derived breaks in trend is an appropriate variable for explaining long-term trends.

Chapter 2 - Literature Review

Environmental Monitoring

Ecosystems all around the world are in a constant state of change at different spatial scales due to both natural and anthropogenic causes (Millennium Ecosystem Assessment 2005). Current trends in ecosystem management are often centered on the idea of sustainability. To support these efforts, accurate monitoring of land-use and land change over large areas and time is required (Coppin *et al.*, 2004). Lack of long-term quantitative land cover data can lead to a misinterpretation of processes that are currently happening and subsequent mismanagement (Lampry 1975). Gradual and abrupt changes in the level of vegetation activity over time can be routinely monitored by collecting and analyzing time-series data from medium and coarse spatial resolution satellite sensors (Beck *et al.,* 2006; Coppin *et al., 2004;* Dash *et al.,* 2010; Julien and Sobrino 2009; Verbesselt *et al.,* 2010a; Verbesselt *et al.,* 2010b).

Times Series Analysis

A time series is defined as "…a sequence of measurements of the same variable collected over time. Most often, the measurements are made at regular time intervals" (Penn State Eberly College of Science 2016, Sec. 1.1). The purpose of a time series model is to "obtain an understanding of the underlying forces and structure that produced the observed data and to fit a model and proceed to forecasting, monitoring or even feedback and feedforward control" (NIST/SEMATECH 2012, Sec. 6.4.1,).

The two basic types of time series models are autoregressive and regression based. A time series analysis can yield important information about a process, including: trend, seasonality, outliers, long-run cycle, constant variance, and abrupt changes. Such results can significantly inform your interpretation of the process by (1) identifying increasing or decreasing trends in the dependent variable, (2) uncovering repeating patterns in the response that correspond to seasonal or other cycles, (3) highlighting the presence of outlying or unusual values, (4) determining whether variance is constant or dynamic, and (5) pinpointing change points where modelled behavior changes significantly (Penn State 2016).

Time series analysis is a technique used by many disciplines/industries. Examples include (NIST/SEMATECH 2012):

- Economic and Sales Forecasting
- Budgetary, Stock Market, and census Analysis
- Yield and Workload Projections
- Process and Quality Control
- Inventory and Utility Studies

Another application of time series analysis is environmental monitoring and classification; it has been a featured method in a number of studies. For example, Yang and Lo (2010) used Landsat imagery to detect land use and land cover changes within the metropolitan area around Atlanta, Georgia. Tatsumi *et al*., (2015) used time series analysis of Landsat 7 images to classify eight different crops (alfalfa, asparagus, avocado, cotton, grape, maize, mango, and tomato) in the Ica region in Peru. Marrari *et al.*, (2016) used high spatial resolution imagery from 1997-2015 to analyze the chlorophyll concentration of the reproductive area of the Argentine hake (*Merluccius hubbsi*).

Remote Sensing

Remote sensing is the process of detecting reflected or emitted electromagnetic radiation (EMR) from Earth's surface which is recorded by sensors onboard aerial or satellite platforms (Ingle *et al*., 2003). Monitoring vegetation cover and vegetation conditions is a necessary task to understand phenomena influenced by vegetation such as terrestrial primary productivity, concentrations of atmospheric CO_2, the hydrologic cycle, and many others. Monitoring vegetation cover and conditions once was, and still is, accomplished via field surveys. However, field surveys can be time intensive and costly, especially if the area of interest is large. Remote sensing helps to overcome the challenges associated with *in-situ* surveying by providing high spatial resolution and multispectral images over long time periods for most areas on Earth (Tucker *et al*., 1985; Cihlar *et al*., 1991).

In its early years, remote sensing of vegetation focused primarily on thematic mapping of different land cover categories and how those categories may be changing over time. Over time, advancements in technology has allowed sensors and computer-based analyses to also extract a number of biophysical parameters about the earth's surface (Underwood 2006).

There are many different sensors that are useful for monitoring the terrestrial environment. Table 1 lists a number of these sensors and some of their important operational characteristics.

Sensor	Satellite Platform	Spatial Resolution	Swath Width	Spectral Bands (nm)
AVHRR	NOAA-POES	1.1 km	2,700 km	580-680 725-1,000 1,580-1,640 3,550-3,930 10,300-11,300 11,500-12,500
POLDER	ADEOS	6 km	2,400 km	433-453 555-575 660-680 845-885
MODIS	Terra and aqua	500 m 500 m 250 m 250 m 500 m 500 m 500 m 1 km 1 km 1 km	2,330 km	459-479 545-565 620-670 841-876 1,230-1,250 1,628-1,652 2,105-2,155 3,929-3,989 10,780-11,280 11,770-12,270
MERIS	Envisat	300 m 1.2 km	575 km 1150 km	660-670 855-875

Table 1 Moderate to coarse resolution sensors onboard satellites commonly used for environmental remote sensing with their key operating characteristics (adapted from Townshend and Justice 2002).

Remote sensing of vegetation has occurred on a global scale since the early 1980's (Schwartz 1998) with the launch of the Advanced Very High Resolution Radiometer (AVHRR) sensor onboard NOAA-POES in 1981. The MODIS sensor followed, first with a launch in 1999 onboard the Terra satellite and then another in 2002 onboard the Aqua satellite (Townshend and Justice 2002). The next sensor, VIIRS, was supposed to go up on March 31, 2014 onboard the National Polar-orbiting Operational Environmental Satellite System (NPOESS), but as of 2016 is still listed as in "Development". It is expected to improve upon the AVHRR and MODIS sensors increase the capabilities of the operational environmental monitoring satellite system (NASA 2013).

MODIS

The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor is on board both the Terra and Aqua satellites which comprise part of the Earth Observing System (EOS). The EOS system and program is designed to study the role of vegetation in large-scale processes for better understanding how the Earth functions as a system (Huete *et al*., 2002). Compared to the AVHRR, MODIS sensors offer increased spatial resolution, more precise bandwidths, and a greater number of spectral channels (Townshend and Justice 2002). The Terra and Aqua satellites are in a sun-synchronous and near-polar circular orbit and covers the entire Earth's surface every 1-2 days. Terra crosses the equator from north-to-south at approximately 10:30 a.m. local time followed by Aqua (from south-to-north) at 1:30 p.m. Their MODIS sensors have a whiskbroom scanner that collects 36 co-registered spectral bands with a field of view of +/- 55° off-nadir, and a swath width of 2,330 km (Jensen 2000). MODIS has one of the best and most comprehensive calibration subsystems on a remote sensing instrument including a solar diffuser, a spectroradiometric calibration instrument, a solar diffuser stability monitor, a space viewport, and a blackbody for thermal calibration (Jensen 2000, p. 231).

Landsat 5 Multispectral Scanner / Thematic Mapper

The Landsat 5 Multispectral Scanner (MSS) and Thematic Mapper (TM) was launched in 1984 with a design life of 5 years. Operational imaging ended in November 2011 and the satellite was officially decommissioned on June 5, 2013 (U.S. Geological Survey 2013b). Landsat 5 TM was in sun-synchronous, near-polar orbit (altitude of 705 km), inclined at 98.2°, had a 16 day repeat cycle, and a swath width of 185 km organized in the WRS-2 path/row system. The operating characteristics of the MSS and TM sensors are listed in Table 2.

Sensor	Band Number	Spectral Bandwith (μm)	EMR Spectrum	Spatial Resolution (m)
MSS	1	0.5-0.6	Visible	60
	2	0.6-0.7	Visible/Near-Infrared	60
	3	0.7-0.8	Near-Infrared	60
	4	0.8-1.1	Near-Infrared	60
TM	1	0.45-0.52	Visible	30
	2	0.52-0.60	Visible	30
	3	0.63-0.69	Visible	30
	4	0.76-0.90	Near-Infrared	30
	5	1.55-1.75	Near-Infrared	30
	6	10.40-12.50	Thermal	120
	7	2.08-2.35	Mid-Infrared	30

Table 2 Operating characteristics of the Multispectral Scanner (MSS) and Thematic Mapper (TM) sensors onboard the Landsat 5 satellite (U.S. Geological Survey 2014).

Landsat 5 imagery has been used for a variety of purposes, including to measure surface temperature (Sobrino 2004), detect burn scars (Koutsias *et al.*, 2000; Hudak *et al.*, 2004; Mohler 2011), monitor landuse change (Seto *et al.*, 2002), show coastal effects of hurricanes (Barras 2006), identify geomorphic features (Novak *et al*., 2000), and model glacial hazards (Huggel *et al*., 2004).

Landsat 7 Enhanced Thematic Mapper Plus

Landsat 7 ETM+ was launched in 1999 and is still gathering data today (NASA 2010). Landsat 7 ETM+ is in sun-synchronous, near-polar orbit (altitude of 705 km), inclined at 98.2°, has a 16 day repeat cycle, a swath width of 185 km and, like Landsat 5, uses the WRS-2 path/row system. The operating characteristics of the eight-band ETM+ sensor is listed in Table 3.

Sensor	Band Number	Spectral Bandwith (μm)	Spectral Bandwith (μm)	Spatial Resolution (m)
ETM+	1	0.45-0.52	Visible	30
	2	0.52-0.60	Visible	30
	3	0.63-0.69	Visible	30
	4	0.77-0.90	Near-Infrared	30
	5	1.55-1.75	Near-Infrared	30
	6	10.40-12.50	Thermal	60
	7	2.09-2.35	Mid-Infrared	30
	8	0.52-0.90	Panchromatic	15

Table 3 Operating characteristics of the Enhanced Thematic Mapper Plus (ETM+) sensor onboard the Landsat 7 satellite (U.S. Geological Survey 2013a).

Since May 2003, Landsat 7 scenes suffer from a scan line corrector defect that causes data gaps (i.e., striping) in images (U.S. Geological Survey 2015). Though a given image now only contains 78% of their pixels, ETM+ data is still a valuable data source (U.S. Geological Survey 2013). Examples of applications from past studies incorporating ETM+ images include landuse and landcover change detection (Yang *et al.*, 2002), detecting of coal mine fires (Mishra *et al*., 2011), mapping abundance and distribution of animals (Lynch *et al.*, 2014), and crop classification (Tatsumi *et al.,* 2015).

Normalized Difference Vegetation Index

Normalized difference vegetation index (NDVI) is a vegetation condition metric derived from satellite imagery to provide information about vegetation and vegetation change (Wright *et al*., 2012). A measure of "greenness", NDVI has been shown to correlate with a number of biophysical variables such as leaf-area index (LAI), percent cover, and aboveground biomass and has been used in a number of environmental remote sensing studies (Cihlar *et al*., 1991; Petterelli *et al*. 2005; Tucker *et al*., 1991). It has also been suggested that NDVI relates to photosynthesis and transpiration (Running 1988).

Extracting NDVI values for an area over a long time period allows valuable information about vegetation conditions to be inferred. NDVI values gathered throughout a growing season can also be used to estimate a phenological development curve for the different vegetation types. Once such a curve is created, it is possible to identify key "phenometrics" such as the dates for the onset and end of a growing season, the magnitude and time when maximum NDVI is achieved, and growing season length (de Jong *et al*., 2011).

NDVI values are calculated as a ratio of red to near-infrared reflectance and ranges between -1 and +1 (Equation 1). Negative numbers relate to the absence of vegetation and the more positive the number the greener the vegetation. There are many different NDVI data sets available with different temporal and spatial resolutions (Pettorelli *et al*., 2005). Table 4 lists some examples.

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Equation 1 NDVI Equation

Satellite Sensor	Date Range	Spatial Resolution
AVHRR	1981-Present	8-16 km
Landsat 5-8	1984-Present	30-60 m
SPOT 1-7	1986-Present	6-20 m
MODIS	2000-Present	250-1000 m

Table 4 Commonly used long-term NDVI datasets (from Pettorelli *et al*. 2005).

NDVI will increase quite quickly in the spring and will decrease from the middle to end of summer through fall (Cihlar *et al*., 1991). Changes in NDVI suggest that vegetation is responding differently given variations in how photosynthetically active radiation is being absorbed or reflected (Sellers 1985). Because NDVI is dependent on reflected EMR from the visible and NIR spectrum, many things can interfere with the response reaching the sensor and affect the recorded data. Examples of such interference include atmospheric effects, satellite drift, calibration issues, clouds, bare soil, and smoke from fires (Gutman and Ignatov 1995; Privette *et al*., 1995; Heute and Jackson 1988; De Moura and Galvao 2003). Another known issue with the ratio-based NDVI is that its response is non-linear, especially at its upper (very green) end. At high NDVI values, even a small change might actually represent a significant difference in the vegetation.

BFAST

Among methods for analyzing trends in continuous vegetation index time series datasets, temporal decomposition techniques have been shown relevant to the study of vegetation seasonality (Jönsson and Eklundh 2002) and the detection of vegetation changes as they relate to agricultural practices (Millward *et al*., 2006), gradual interannual vegetation change due to rainfall variability and drought (Jacquin *et al*., 2010; Fensholt *et al*., 2009; Lambert *et al*., 2013), and abrupt vegetation change observed at the intraannual time scale caused by disturbances such as fire, disease and insect outbreaks, deforestation, and construction activities (Verbesselt *et al*., 2010a). Temporal decomposition separates the original time series dataset into three different components, each of which may be related to vegetation condition at different time scales (Brockwell and Davis 1996; Cleveland and Delvin 1988):

(1) Seasonal – annual or seasonal

(2) Trend – multi-annual linear or nonlinear with, or without, breakpoints

(3) Noise – residuals remaining after elimination of trend and seasonal components

The Breaks For Additive Seasonal and Trend (BFAST) approach was selected as the temporal decomposition method because of its ability to account for seasonality and to detect gradual interannual and abrupt intraannual changes within the trend component (Verbesselt *et* *al*., 2010a). Four additional characteristics make BFAST appropriate for near real-time global scale disturbance detection (Verbesselt *et al*., 2012):

(1) It is fast and requires a minimum amount of processing time

(2) It does not require definition of thresholds

(3) There can be gaps in the data and it can still be analyzed

(4) It analyzes full temporal detail of a time series

BFAST has been used with time series MODIS 16-day NDVI composite imagery in Australia to accurately detect abrupt changes in forests, to detect the magnitude of the change, and to determine if the detected change was positive or negative (Verbesselt *et al*., 2010b). The same MODIS imagery and BFAST have also been used to look at the phenological change in grasslands and plantations in Australia (Verbesselt *et al*., 2010b). BFAST has also been used to look at global vegetation trends (de Jong *et al*., 2013), vegetation trends at a military installation (Hutchinson *et al*., 2015), and tested against other trend models in Alaska (Forkel *et al*., 2013).

Burn Analysis

Burning prairies for management purposes has been done for over one hundred years and is important for their continued viability (Vogl 1974, Towne and Owensby 1984). Benefits of grassland burning include promoting native vegetation and decreasing litter cover (Herndon and Taylor 1986; Shay *et al*., 2001; Hulbert 1969). Burning is an important step within the cycle that makes up grassland ecosystems. Without fires, prairies would most likely be overtaken by woody vegetation. Fires dry out soil moisture needed for tree seeds to sprout and also kill saplings (Stewart 1951, Hulbert 1969). The frequency of fires can also have an effect on vegetation composition (Shay *et al*., 2001) allowing different types of grasses to establish.

Being able to detect burns over large areas is of interest to many people for forest monitoring, prairie management, carbon cycle studies, air quality management, and habitat quality assessment (Bourgeau-Chavez *et al*., 1997; Towne and Owensby 1984; Dwyer *et al*., 2000; Huang *et al*., 2013; Raynor 2015). Burn detection is frequently done using remotely sensed data (Bourgeau-Chavez *et al*. 1997; Liu *et al*. 2014). Mohler (2011) evaluated multiple approaches across the tallgrass prairie ecoregion and used nine different scenarios that tested the ability of single and multiple bands to detect unburned and burned areas. Mohler's Scenario #7, based on a minimum distance supervised classification with the red and NIR bands was one of the best methods for burn detection in tallgrass prairie.

Military Installations

The U.S. DoD, as of 2012, controls 7,859,618 hectares (ha) of land within the United States (Gorte *et al*., 2012) and a total of over 11 million ha worldwide. The DoD controls land in all 50 states, seven U.S. territories, and 40 foreign countries (Base Structure Report 2012). Since the inception of the U.S. Army, Navy, and Marine Corps in 1775 and with the establishment of The War Department (later the Department of Defense) in 1789 there has been military training activities occurring on U.S. soil, in some areas, for over 200 hundred years. The DoD, as of 2013, has 1.4 million active duty men and women in the armed forces and 718,000 civilian personnel and is the nation's largest employer (U.S. Department of Defense 2013). The mission of the DoD is to, "provide the military forces needed to deter war and to protect the security of our country (U.S. Department of Defense 2013)."

Across all DoD lands, there are 4,451 DoD sites split between Army, Navy, Air Force, Marine Corps, and Washington Headquarter Services (Base Structure Report 2012). These sites support a variety of training activities, including light and heavy vehicle maneuvering (*e.g.*, Growler, Humvee, Bradley, tanks), dismounted infantry exercises, air to ground missile strikes, gunnery ranges, and search and rescue simulations.

According to the DoD Base Structure Report (2012) produced by the Office of the Deputy Under Secretary of Defense (Installations & Environment), the DoD has a total of 111 large sites in the U.S. with 103 medium sites, 3803 small sites, and 434 other sites for a total of 4,451 sites. To be qualified as a large site, the installation has to have a Plant Replacement Value (PRV) that is greater than or equal to $1.715 billion (Base Structure Report 2012, p. 27). The total PRV for only the 111 large sites is a minimum of $190 billion. Kansas has two sites that qualify as large sites: Fort Riley (41,180 ha, PRV 4.6 billion) and Fort Leavenworth (2,281 ha, PRV 2.6 billion). The study area for this study is the Smoky Hill ANGR near Salina, Kansas. It spans 13,709 ha and has a PRV of $75.3 million. There are 98 active duty personal at Smoky Hill ANGR (Base Structure Report 2012).

Training that takes place at DoD installations can adversely impact the environment, but is essential in preparing soldiers for their wartime missions. The many different military training activities at DoD sites have been shown to have dramatic impacts on the environment (Shaw *et al*., 1989). Some of these impacts are soil compaction and erosion, native vegetation decrease, alien vegetation increase, soil chemistry changes, and aquatic community disturbances (Wilson 1988; Quist *et al*., 2003; Whitecotton *et al*., 2000). Environmental policy and regulations for military installations started in the late 1960's with *military environmentalism* (Coates *et al*., 2011).

During the 1960's and 1970's civilian protestors considered militarization synonymous with destruction and sterility. One way in which the military responded to such protests was to promote the image that military installations were islands of high quality habitat that served as sanctuaries for wildlife. Without military installations, these lands would be taken over by urbanization, tourism, or chemical-fueled agriculture.

In the U.S., starting with the Conservation Programs on Military Reservations (Sikes) Act of 1960, a number of pieces of federal legislation were enacted which required military attention, including the Clean Air Act of 1970, National Environmental Policy Act of 1971, Clean Water Act of 1972, and Endangered Species Act of 1973 (Coates *et al*., 2011). The military had unintentionally become stewards for increasingly valuable biodiversity. In 1983, the DoD created the National Military Fish and Wildlife Association comprised of natural resource experts – nicknamed the "new defenders of wildlife" – as military land management increasingly started to include environmental problem solving (Coates *et al*., 2011). An Army wildlife biologist, James Bailey, said "If we weren't here this land would be all marinas and condominiums" (Cohn 1996, p. 1). He was talking about the Aberdeen Proving Ground on the coast of Maryland and without the military installation being there, there wouldn't be any nature left.

With the passage of the National Environmental Policy Act in 1971, all branches of the U.S. government had to give proper consideration to the environment and prepare Environmental Impact Statements (EIS) before taking any actions that might have an effect on the environment (EPA 2013). Also, Army Regulation 200-2 (Department of the Army 1988) – which applies to the active Army, Army National Guard (ARNG), and the U.S. Army Reserve (USAR) – states that, "this regulation sets forth policy responsibilities, and procedures for integrating environmental considerations into Army planning and decision making…" (Department of the Army 1988, p. 1). An environmental management program that the DoD, U.S. Fish and Wildlife, and state fish and wildlife agencies have developed and amended, in 1997, to the Sikes Act of

1960 is the Integrated Natural Resource Management Plans (INRMPs) (U.S. Department of Defense and U.S. Fish & Wildlife Service 2004).

The Sikes Act of 1960 mandated the development and implementation of management strategies and programs for conserving and protecting biological resources on military lands. INRMPs were developed because military lands present the unique situation where land and water resources are often protected from typical human access and impacts. INRAMPs are defined as:

> "planning documents that allow DoD installations to implement landscape-level management of their natural resources… extremely important management tools that ensure military operations and natural resources conservation are integrated and consistent with stewardship and legal requirements (U.S. Department of Defense and U.S. Fish & Wildlife Service 2004, p. 1)."

According to British geographer Martin Coulson a member of NATO's Committee on the Challenges of Modern Society (CCMS), 1969 was a catalyst for military environmentalism with the issuing of an Environmental Principles Statement in 1990 and the NATO Environmental Policy Statement for the Armed Forces in 1993. The NATO Environmental Policy Statement for the Armed Forces contained videos and leaflets that talked about soldiers training "green" and initiated courses (1995-present) in environmental management of military lands at the NATO school in Oberammergau, Germany (Coates *et al*., 2011).

Many military training activities have impacts on the environment, especially those involving the use of heavy armored vehicles such as tanks. Tank traffic can compact soil, affect soil infiltration rates, change flora composition, increase soil erosion, change wildlife habitat, change soil chemistry, and affect persistent litter (Diersing *et al*., 1988). In the Mojave Desert, tank training activities were still evident in 1982 from General Patton's training in the 1940's, from "Desert Strike" in 1964, and from "Bold Eagle" in 1967 (Lathrop 1982).

In order to balance environmental quality with the need for training lands methods are needed to estimate maximum allowable levels of use without causing significant landscape degradation. In 1988, Scott Wilson of the University of Manitoba, studied the effects of the frequency of tank traffic on prairie ecosystems at the Canadian Forces Base Shilo (Wilson 1988). He discovered that frequency and season in which the tanks were used has different impacts on the mixed grass prairie. Depending on the time of year that the tanks were used, more or less alien grass species would be present. Areas that supported tank traffic only in the summer didn't show any signs of alien grass species. But, areas that were used for tank training in other times of the year (e.g., spring) saw an increase in non-natives that led to a shift in the local composition prairie grasses. Further, increasing bare ground was correlated with higher frequencies of tank training. Through this type of analysis, Wilson (1988) developed a predictive management model to show what vegetation would be like with differences in tank traffic.

Similar work that studied the impact of maneuver training on different vegetation and soils has also been done across the U.S., including the Cross Timbers region in central Texas (Severinghaus *et al.*, 1981), the Mojave Desert in southern California (Lathrop 1982), southeastern Colorado's shortgrass steppe (Milchunas *et al.*, 1999), northeastern Kansas's tallgrass prairie in northeastern Kansas (Quist *et al.*, 2003; Althoff *et al.,* 2009), and mixed grass prairie in southwestern Oklahoma (Leis *et al.,* 2005).

Chapter 3 - Study Area

Overview

Smoky Hill Air National Guard Range (ANGR) is a 13,708 hectare (ha) range located southwest of Salina, Kansas. The site is located mostly within Saline County, but the extreme southern edge of the range falls within McPherson County (Figure 1). The site is also situated in the Smoky Hills ecoregion of Kansas (Hansen 2012), a 2,028,997 ha transition area comprised of tallgrass prairie in the east to mixed grass prairie in the west (Busby *et al*., 2007) (Figure 2).

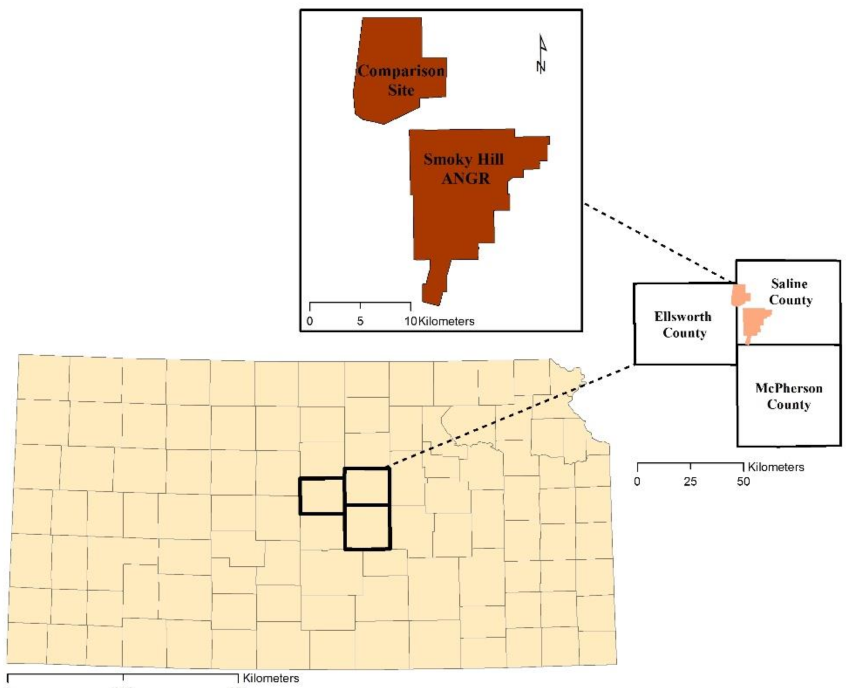

Figure 1 Study area map highlighting the location of the Smoky Hill Air National Guard Range (ANGR) and the Comparison Site used in this study.

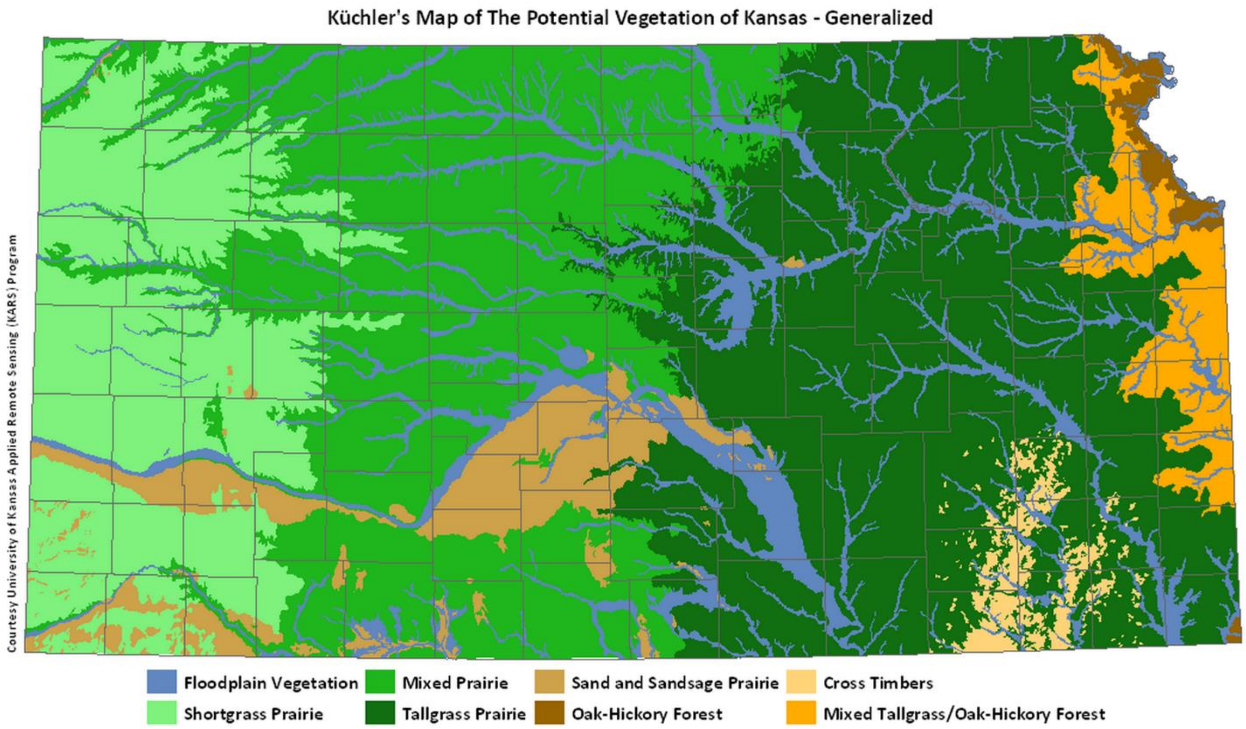

Figure 2 Generalized potential natural vegetation map of Kansas (from Küchler 1974).

Smoky Hill ANGR is used almost exclusively (estimated 90% of use) by the Kansas Air National Guard (KSANG). It also sees some use (estimated 10% of use) by the Kansas Army National Guard (KSARNG). Occupying the center of the range is a 4,091 ha Impact Area for air-to-ground bomb training (Busby *et al*., 2007).

In 1860, a Saline County land survey reported that 99% of the original vegetation at Smoky Hill ANGR was tallgrass prairie. There were no developed forests and there were only small areas (37 ha) of riparian forest. From the late 1850’s to just before U.S. involvement in World War II, the site was sparsely settled and used primarily for crop production and livestock grazing (Pike 2011).

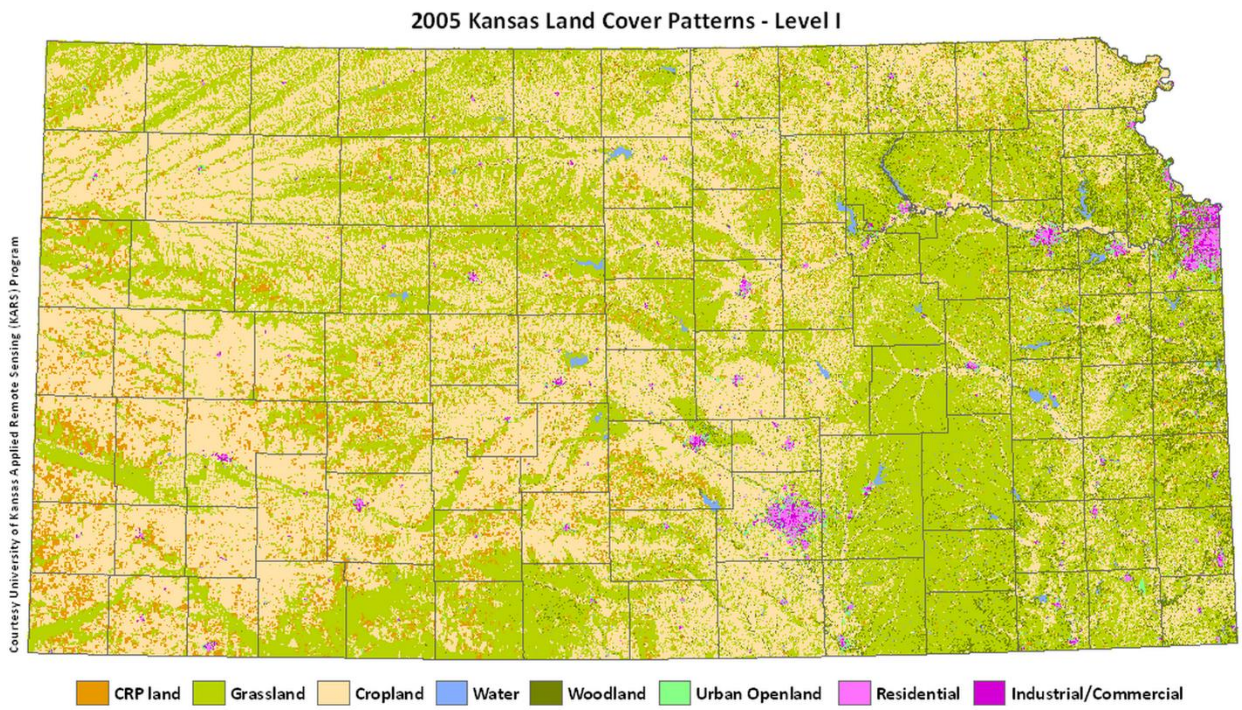

Figure 3 General landuse/landcover map of Kansas (Kansas Applied Remote Sensing Program 2005).

Smoky Hill ANGR vegetation at present time is mostly Dakota Hills Tallgrass Prairie (Figure 3). The underlying geology is comprised of sandstone, shale, loamy colluvium (Hansen 2012). The climate at the range is temperate continental with large temperature swings. The average annual precipitation is 75.9 cm (Figure 4) and average temperature is 12.9ºC (NCDC 2013).

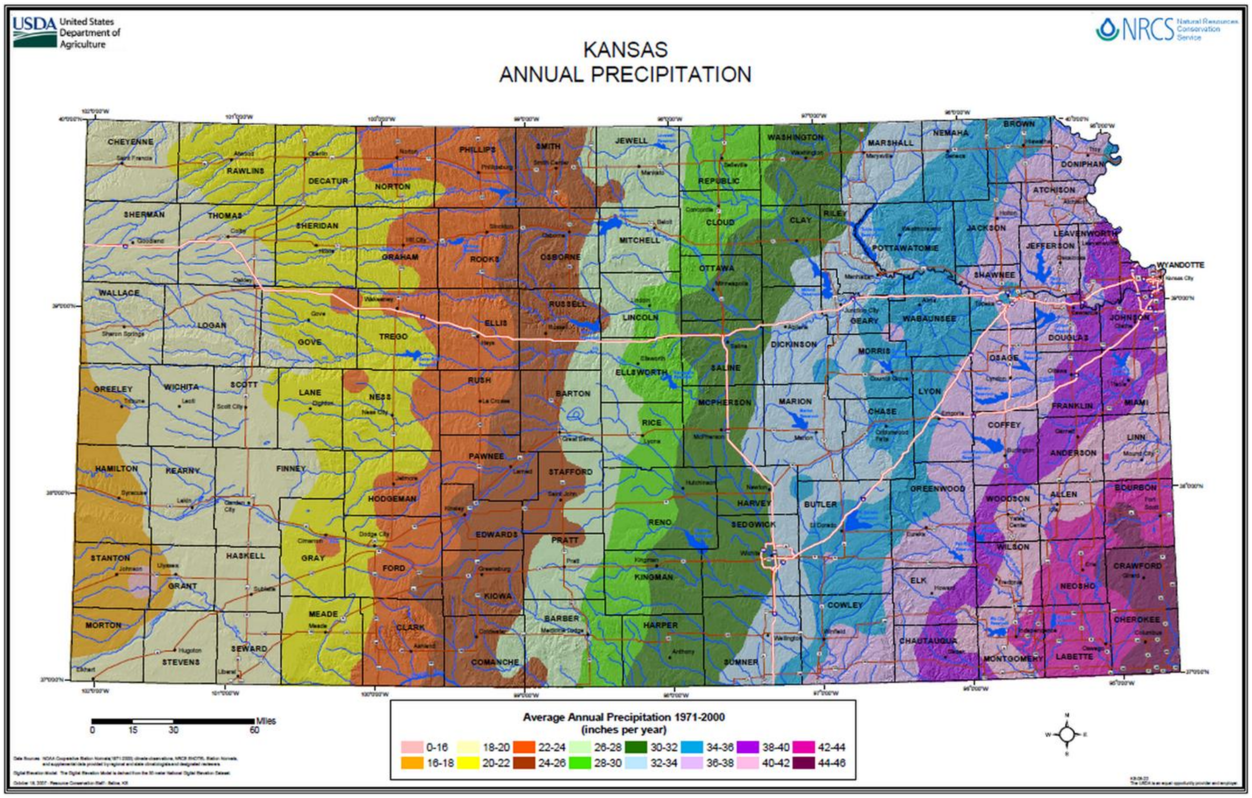

Figure 4 Average annual precipitation in Kansas (NRCS 2007).

Weather Data

Daily weather data was gathered for January 2001-December 2011, from Weather Underground (www.wunderground.com/history), for the Salina Municipal Airport located roughly 16 km to the North East of Smoky Hill ANGR. This weather data is the closest geographically to the study area that has all the necessary weather measures for the needed time period. The average monthly temperature, maximum and minimum monthly temperature, and monthly total precipitation were generated from the daily data.

The monthly data was charted and trend analyzed for mean monthly temperature, maximum monthly temperature, minimum monthly temperature, and total monthly precipitation. A Student t-test was run on all four weather measurements to determine if the slope of the trend line was significantly different from null. The results of the Student t-test showed there was no significant difference from null for all four weather measurements. The mean monthly temperature, maximum monthly temperature, minimum monthly temperature, and total monthly precipitation were stable from 2001-2011.

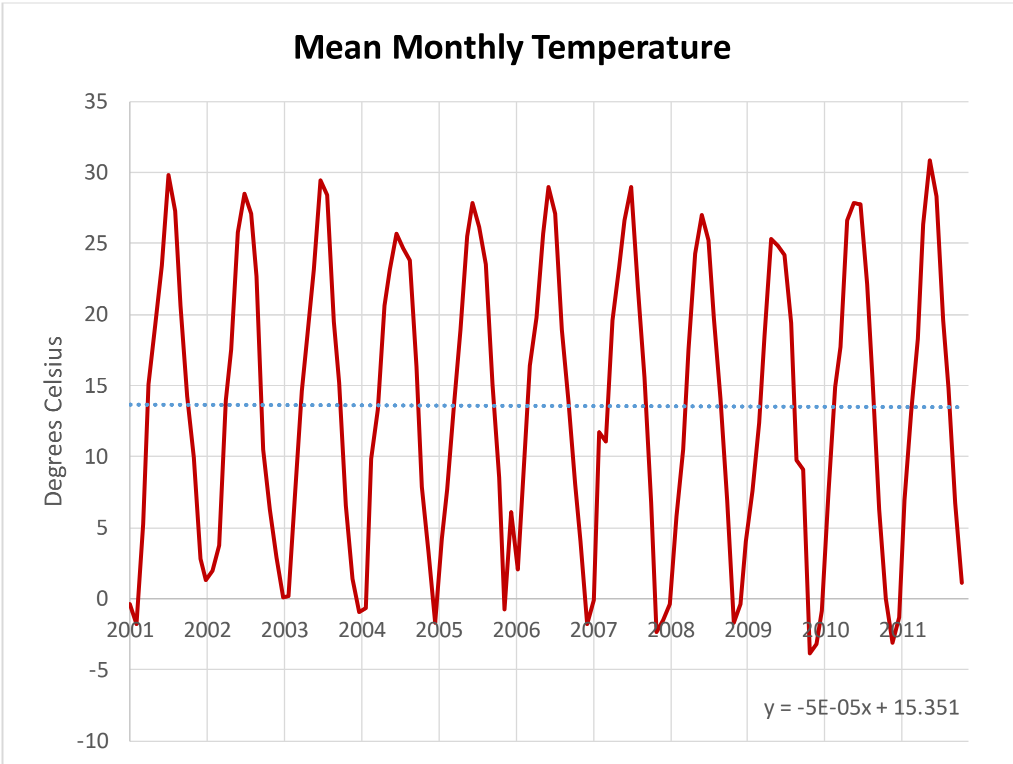

Figure 5 Graph of the Mean Monthly Temperature from January 2001 – December 2011 for the Salina Municipal Airport near Smoky Hill ANGR data from Weather Underground 2016.

	Mean Monthly Temperature °Celsius										
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
January	-0.3	1.3	0.1	-1.0	-1.7	6.0	-1.8	-1.5	-0.4	-3.2	-3.1
February	-1.8	2.0	0.2	-0.7	4.2	2.1	-0.1	-0.3	4.0	-0.8	-1.3
March	5.2	3.7	7.5	9.8	7.7	8.4	11.7	5.8	7.6	7.5	6.9
April	15.1	13.9	14.6	13.3	13.5	16.4	11.1	10.5	12.4	14.9	13.1
May	19.2	17.5	18.4	20.7	18.9	19.8	19.6	17.5	18.4	17.7	18.2
June	23.4	25.7	23.2	23.2	25.5	25.6	23.4	24.3	25.3	26.6	26.3
July	29.8	28.5	29.4	25.7	27.8	29.0	26.6	27.0	24.9	27.9	30.9
August	27.3	27.1	28.4	24.6	26.1	27.1	28.9	25.3	24.2	27.7	28.3
September	20.6	22.7	19.5	23.8	23.5	18.9	21.9	19.8	19.4	22.1	19.6
October	14.3	10.5	15.2	16.3	15.1	13.9	15.5	14.1	9.7	15.5	14.8
November	10.0	6.3	6.5	7.9	8.5	8.1	6.7	6.9	9.1	6.3	6.8
December	2.8	2.8	1.4	3.2	-0.8	4.0	-2.3	-1.7	-3.8	0.0	1.1

Table 5 The Mean Monthly Temperatures for every month from 2001-2011 at the Salina Municipal Airport near Smoky Hill ANGR data form Weather Underground 2016.

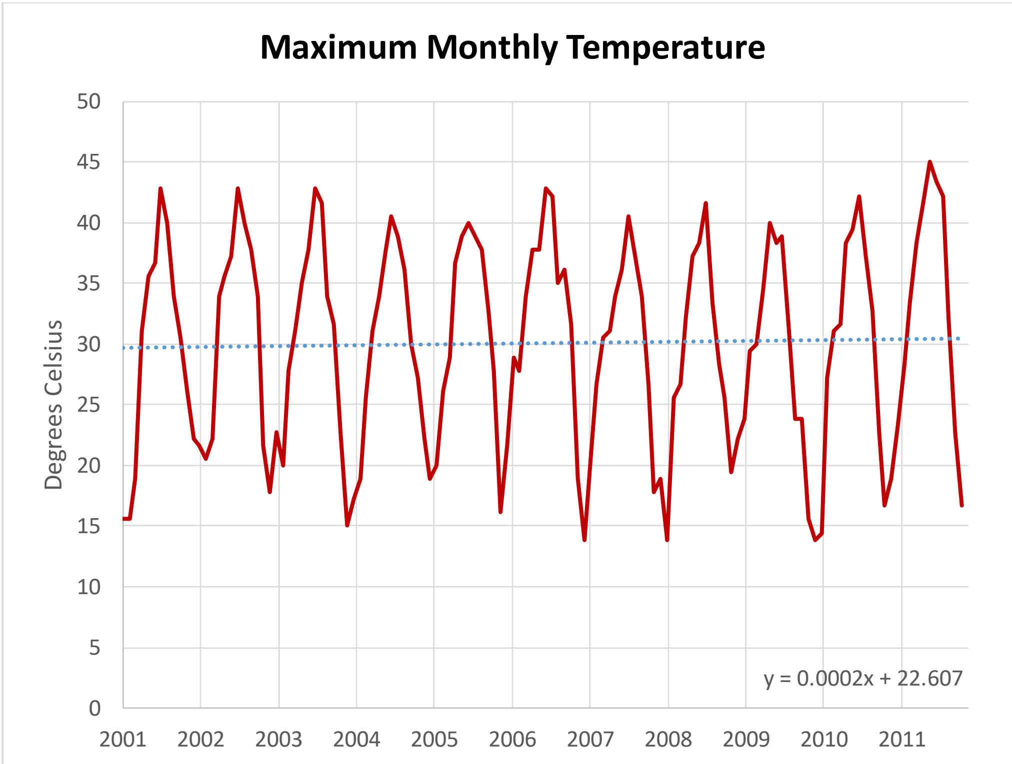

Figure 6 Graph of the Maximum Monthly Temperature from January 2001 – December 2011 for the Salina Municipal Airport near Smoky Hill ANGR data from Weather Underground 2016.

	Maximum Monthly Temperature °Celsius										
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
January	15.6	21.7	22.8	17.2	18.9	21.7	13.9	18.9	22.2	13.9	18.9
February	15.6	20.6	20.0	18.9	20.0	28.9	21.1	13.9	23.9	14.4	23.3
March	18.9	22.2	27.8	25.6	26.1	27.8	26.7	25.6	29.4	27.2	28.3
April	31.1	33.9	31.1	31.1	28.9	33.9	30.6	26.7	30.0	31.1	33.3
May	35.6	35.6	35.0	33.9	36.7	37.8	31.1	32.2	34.4	31.7	38.3
June	36.7	37.2	37.8	37.8	38.9	37.8	33.9	37.2	40.0	38.3	41.7
July	42.8	42.8	42.8	40.6	40.0	42.8	36.1	38.3	38.3	39.4	45.0
August	40.0	40.0	41.7	38.9	38.9	42.2	40.6	41.7	38.9	42.2	43.3
September	33.9	37.8	33.9	36.1	37.8	35.0	37.2	33.3	31.7	37.2	42.2
October	30.6	33.9	31.7	30.0	32.8	36.1	33.9	28.3	23.9	32.8	32.2
November	26.1	21.7	22.8	27.2	27.8	31.7	26.7	25.6	23.9	22.8	22.8
December	22.2	17.8	15.0	22.2	16.1	18.9	17.8	19.4	15.6	16.7	16.7

Table 6 The Maximum Monthly Temperatures for every month from 2001-2011 at the Salina Municipal Airport near Smoky Hill ANGR data from Weather Underground 2016.

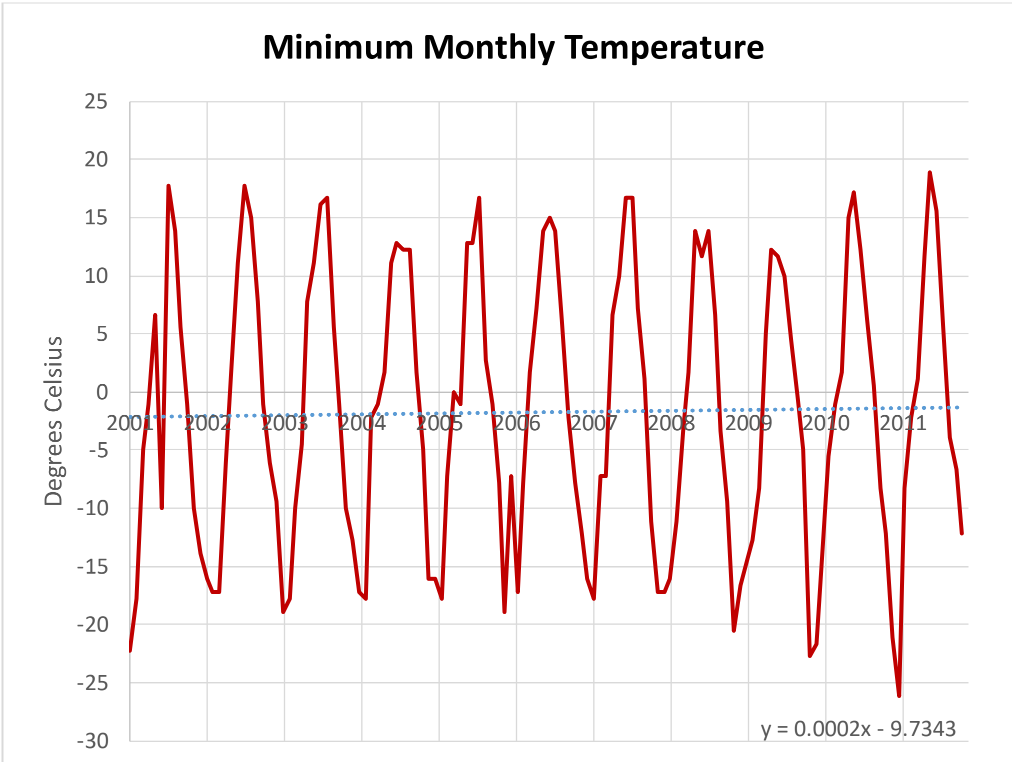

Figure 7 Graph of the Minimum Monthly Temperature from January 2001 – December 2011 for the Salina Municipal Airport near Smoky Hill ANGR data from Weather Underground 2016.

	Minimum Monthly Temperature °Celsius										
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
January	-22.2	-16.1	-18.9	-17.2	-16.1	-7.2	-16.1	-17.2	-16.7	-21.7	-21.1
February	-17.8	-17.2	-17.8	-17.8	-17.8	-17.2	-17.8	-16.1	-14.4	-12.8	-26.1
March	-5.0	-17.2	-10.0	-2.2	-7.2	-7.8	-7.2	-11.1	-12.8	-5.6	-8.3
April	-1.1	-6.1	-4.4	-1.1	0.0	1.7	-7.2	-3.3	-8.3	-1.1	-2.2
May	6.7	1.7	7.8	1.7	-1.1	7.2	6.7	1.7	5.0	1.7	1.1
June	-10.0	11.1	11.1	11.1	12.8	13.9	10.0	13.9	12.2	15.0	11.7
July	17.8	17.8	16.1	12.8	12.8	15.0	16.7	11.7	11.7	17.2	18.9
August	13.9	15.0	16.7	12.2	16.7	13.9	16.7	13.9	10.0	12.2	15.6
September	5.6	7.8	5.6	12.2	2.8	6.1	7.2	6.7	4.4	6.1	5.6
October	-1.1	-1.1	-1.1	1.7	-1.1	-2.2	1.1	-3.3	-0.6	0.6	-3.9
November	-10.0	-6.1	-10.0	-5.0	-7.8	-7.8	-11.1	-9.4	-5.0	-8.3	-6.7
December	-13.9	-9.4	-12.8	-16.1	-18.9	-12.2	-17.2	-20.6	-22.8	-12.2	-12.2

Table 7 The Minimum Monthly Temperatures for every month from 2001-2011 at the Salina Municipal Airport near Smoky Hill ANGR data from Weather Underground 2016.

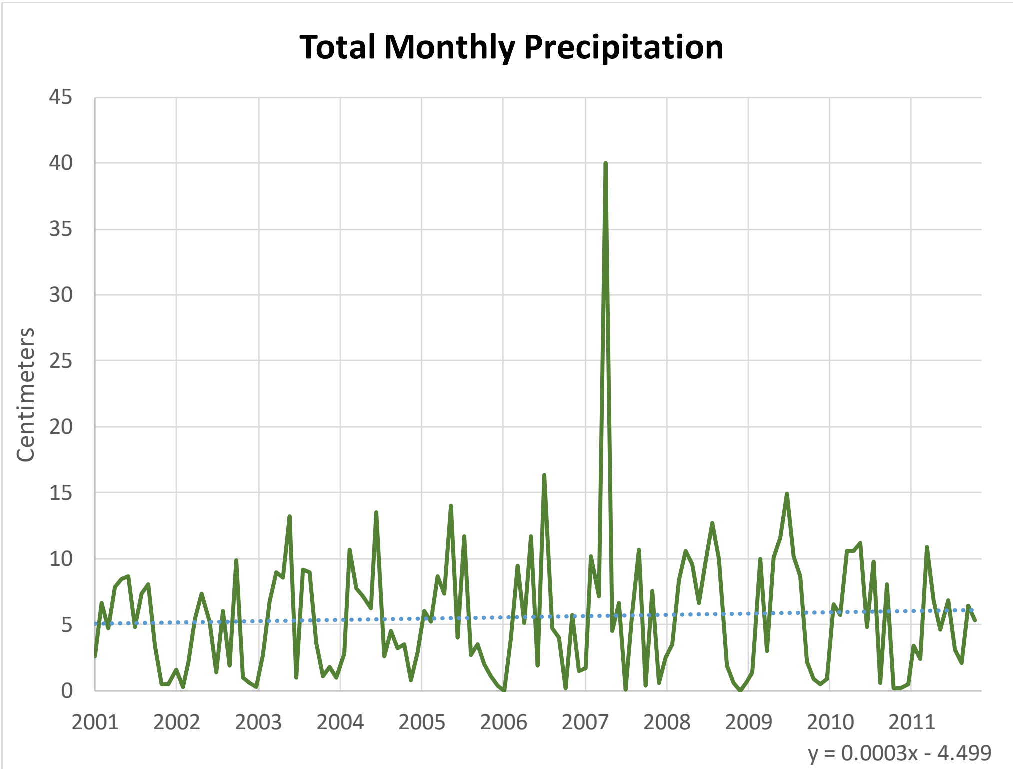

Figure 8 Graph of the Total Monthly Precipitation from January 2001 – December 2011 for the Salina Municipal Airport near Smoky Hill ANGR data from Weather Underground 2016).

	Total Monthly Precipitation Centimeters (Cm)										
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
January	2.64	1.60	0.33	0.94	2.90	0.36	1.52	0.56	0.00	0.53	0.23
February	6.68	0.33	2.74	2.82	6.07	0.00	1.70	2.51	0.66	0.84	0.46
March	4.70	2.08	6.78	10.72	5.21	4.06	10.21	3.48	1.42	6.58	3.43
April	7.85	5.49	8.97	7.75	8.64	9.47	7.19	8.33	10.03	5.77	2.36
May	8.48	7.32	8.61	7.14	7.37	5.11	39.98	10.57	3.05	10.57	10.92
June	8.66	5.26	13.23	6.25	14.00	11.73	4.52	9.60	10.08	10.57	6.81
July	4.88	1.42	0.94	13.49	4.04	1.91	6.60	6.65	11.61	11.15	4.60
August	7.39	5.99	9.19	2.64	11.73	16.38	0.10	9.75	14.99	4.88	6.86
September	8.10	1.88	8.97	4.57	2.72	4.72	5.97	12.75	10.19	9.75	3.15
October	3.45	9.86	3.61	3.18	3.53	4.01	10.67	9.96	8.64	0.58	2.08
November	0.48	0.97	1.04	3.53	2.01	0.15	0.36	1.88	2.18	8.08	6.45
December	0.51	0.56	1.78	0.76	1.07	5.77	7.54	0.58	0.89	0.15	5.31

Table 8 The Total Monthly Precipitation for every month from 2001-2011 at the Salina Municipal Airport near Smoky Hill ANGR data from Weather Underground 2016.

Military Training

The Smoky Hill ANGR area dramatically changed in 1942 when military control of the site began. Due to the military occupation, land use on the range changed with most cropland being converted back to grassland. However, only for a short period during WWII , when the range was Camp Phillips (1942-1944), was there intense training over the whole range (Figure 9) (Pike 2011).

Figure 9 Smoky Hill ANGR, then known as Camp Phillips, in 1942 (image courtesy of the Kansas Historical Society).

At present, Smoky Hill ANGR is the largest bombing range in the nation with over 100 tactical targets. The live bombing range is only a portion of the overall range and outside of that area there is only moderate training activities and several agricultural and livestock leases

(Busby *et al*., 2007). The range is currently controlled by the 184th Bomb Group, Kansas Air National Guard (Pike 2011).

Figure 10 Examples of training activates conducted at Smoky Hill ANGR (Kansas Adjutant General's Department 2011).

Environmental Management

In compliance with DoD policy, an Integrated Natural Resource Management Plan (INRMP) was implemented at Smoky Hill ANGR (Engineering-Environmental Management, Inc. 2007). Installation-specific INRMP guides ecosystem management within military mission requirements and, at Smoky Hill ANGR, also governs livestock and agricultural leases (Busby *et al.*, 2007). The goals for natural resource management at Smoky Hill ANGR are "to enhance and maintain biological diversity within the Range boundaries, while assuring the successful accomplishment of the military mission. Management practices should minimize habitat fragmentation and promote the natural pattern and connectivity of habitats; protect rare and ecologically important species; maintain and mimic natural processes; and restore species, communities, and ecosystems (Busby *et al*., 2007, p. 7)".

In 2002, Smoky Hill ANGR asked the Kansas Biological Survey (KBS) to do conduct an inventory of the flora and fauna for their training lands and to rate the overall ecological condition at the range (Busby *et al*., 2007). The KBS concluded that Smoky Hill ANGR is an example of a large preserved tallgrass prairie with large spans of unbroken prairie that serves as a hotspot for biodiversity for the Great Plains. Overall, KBS categorized the grassland communities as “good” because of their thoughtful management practices . A goal for the INRMP is to raise the overall quality from “good” to “excellent” (Busby *et al*., 2007).

Comparison Site

A comparison site located approximately 16 km northwest of Smoky Hill ANGR was identified for this study. The Comparison Site is a 7,351 ha, large unbroken area of grassland used for grazing cattle, has very little cropland, and few houses or roads. It is in the same ecoregion as Smoky Hill ANGR and, due to its proximity to the military site, is assumed to have the same weather and climate conditions. Figure 11 again shows the location of Smoky Hill ANGR and the Comparison Site with a background satellite image showing the proximity of the sites and similar landcover conditions.

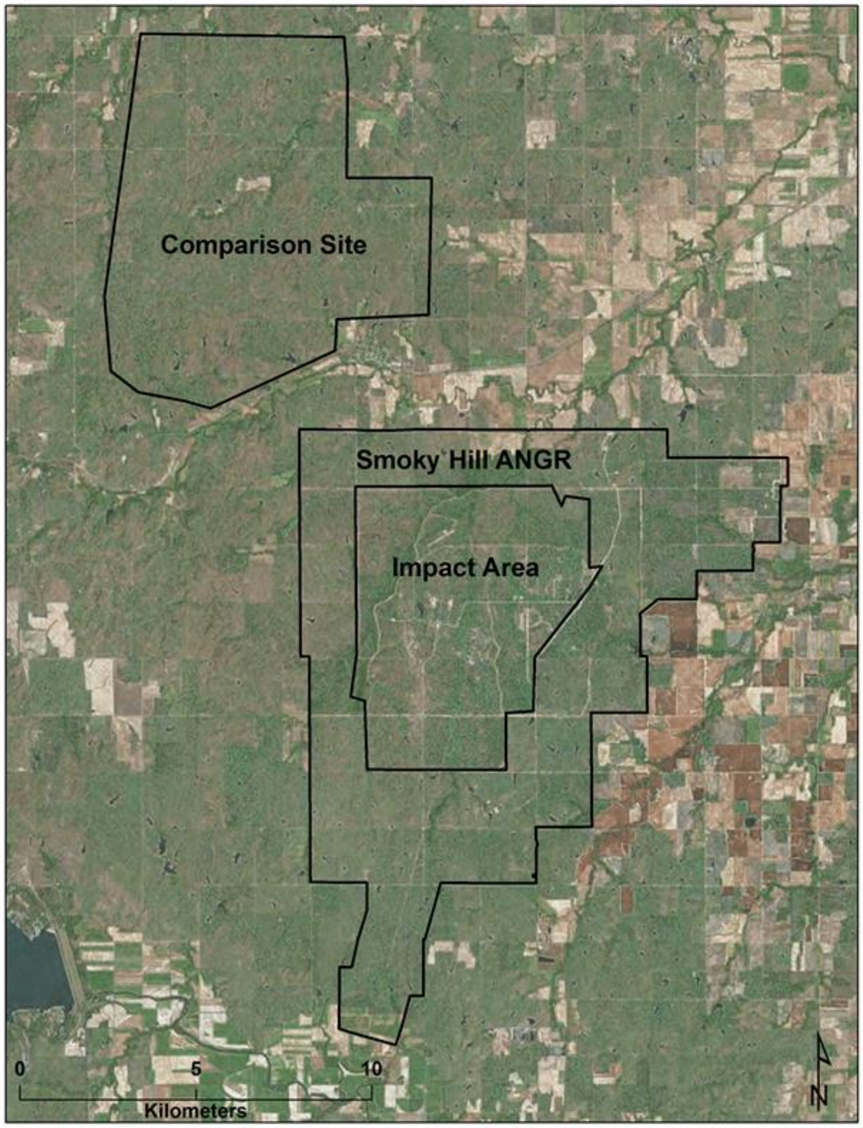

Figure 11 Detailed view of the Smoky Hill ANGR and Comparison Site. This image highlights the 4,091 ha Impact Area internal to Smoky Hill ANGR (image courtesy of the Environmental Systems Research Institute, Esri).

Chapter 4 - Development of a Contemporary Burn History of Smoky Hill Air National Guard Range using Landsat 5 and 7 Imagery

Abstract

Military installations are important assets for the proper training of armed forces. To ensure the continued viability of training lands, management practices need to be implemented to sustain the necessary environmental conditions for safe and effective training. This analysis uses Landsat 5 TM / 7 ETM+ imagery from 2001-2011 to create a burn history at Smoky Hill Air National Guard Range (ANGR), Impact Area (within Smoky Hill ANGR), and a Comparison Site to determine if there are differences in burn regimes. A Minimum Distance Supervised Classification technique was used on the imagery to detect burn scars. After combining individual year burn histories the resulting image was a composite burn frequency history image from 2001-2011 for each of the three study areas. It was found that the entirety of Smoky Hill ANGR burns more frequently than the Comparison Site and most of the burning within Smoky Hill ANGR happens in the Impact Area. This burning may be used for containment of training induced fires or fires starting as a direct result of training. What is not known is if the increase in burn frequency within the Impact Area is causing a different vegetation response than at the Comparison Site.

Introduction

The U.S. DoD, as of 2012, controls 7,859,618 hectares (ha) of land within the United States (Gorte *et al*., 2012) and a total of over 11 million ha worldwide. The DoD controls land in all 50 states, seven U.S. territories, and 40 foreign countries (Base Structure Report 2012). These sites support a variety of training activities, including light and heavy vehicle maneuvering (e.g., Growler, Humvee, Bradley, tanks), dismounted infantry exercises, air to ground missile strikes, gunnery ranges, and search and rescue simulations.

Training that takes place at DoD installations can adversely impact the environment, but is essential in preparing soldiers for their wartime missions. The many different military training activities at DoD sites have been shown to have dramatic impacts on the environment (Shaw *et al*., 1989). Some of these impacts are soil compaction and erosion, native vegetation decrease, alien vegetation increase, soil chemistry changes, and aquatic community disturbances (Wilson 1988; Quist *et al*., 2003; Whitecotton *et al*., 2000).

To help address environmental degradation inherent with military training, and to preserve these areas as safe and realistic training sites, a number of environmental policies and regulations have been established which apply to military organizations and their training lands. Examples of these policies/regulations include the Conservation Programs on Military Reservations (Sikes) Act of 1960, the Clean Air Act of 1970, the National Environmental Policy Act of 1971, the Clean Water Act of 1972, and the Endangered Species Act of 1973 (Coates *et al*., 2011).

With the passage of the National Environmental Policy Act in 1969, all branches of the U.S. government had to give proper consideration to the environment and prepare Environmental Impact Statements (EIS) before taking any actions that might have an effect on the environment

(EPA 2013). In 1983, the DoD created the National Military Fish and Wildlife Association comprised of natural resource experts – nicknamed the "new defenders of wildlife" – as military land management increasingly started to include environmental problem solving (Coates *et al*., 2011). Also, Army Regulation 200-2 (Department of the Army 1988) – which applies to the active Army, Army National Guard (ARNG), and the U.S. Army Reserve (USAR) – states that, "this regulation sets forth policy responsibilities, and procedures for integrating environmental considerations into Army planning and decision making…" (Department of the Army 1988, p. 1).

An environmental management program that the DoD, U.S. Fish and Wildlife, and state fish and wildlife agencies have developed and amended, in 1997, to the Sikes Act of 1960 is the Integrated Natural Resource Management Plans (INRMPs) (U.S. Department of Defense and U.S. Fish & Wildlife Service 2004). INRMPs were developed because military lands present the unique situation where land and water resources are often protected from typical human access and impacts. INRAMPs are defined as:

> "planning documents that allow DoD installations to implement landscape-level management of their natural resources… extremely important management tools that ensure military operations and natural resources conservation are integrated and consistent with stewardship and legal requirements (U.S. Department of Defense and U.S. Fish & Wildlife Service 2004, p. 1)."

For military lands located in prairie landscapes, fire is a common grassland management practice. Wildfires resulting from training activities may also occur throughout the year. Burning prairies for management purposes has been done for over one hundred years and is important for their continued viability (Vogl 1974, Towne and Owensby 1984). Benefits of grassland burning include promoting native vegetation and decreasing litter cover (Herndon and

Taylor 1986; Shay *et al*., 2001; Hulbert 1969). Burning is an important step within the cycle that makes up grassland ecosystems. Without fires, prairies would most likely be overtaken by woody vegetation. Fires dry out soil moisture needed for tree seeds to sprout and also kill saplings (Stewart 1951, Hulbert 1969). The frequency of fires can also have an effect on vegetation composition (Shay *et al*., 2001) allowing different types of grasses to establish.

Background and Objectives

In order to balance environmental quality with the need for training lands methods are needed to estimate maximum allowable levels of use without causing significant landscape degradation. In 1988, Scott Wilson of the University of Manitoba, studied the effects of the frequency of tank traffic on prairie ecosystems at the Canadian Forces Base Shilo (Wilson 1988). He discovered that frequency and season in which the tanks were used has different impacts on the mixed grass prairie. Depending on the time of year that the tanks were used, more or less alien grass species would be present. Areas that supported tank traffic only in the summer didn't show any signs of alien grass species. But, areas that were used for tank training in other times of the year (e.g., spring) saw an increase in non-natives that led to a shift in the local composition prairie grasses. Further, increasing bare ground was correlated with higher frequencies of tank training. Through this type of analysis, Wilson (1988) developed a predictive management model to show what vegetation would be like with differences in tank traffic.

Similar work that studied the impact of maneuver training on different vegetation and soils has also been done across the U.S., including the Cross Timbers region in central Texas (Severinghaus *et al*., 1981), the Mojave Desert in southern California (Lathrop 1982), southeastern Colorado's shortgrass steppe (Milchunas *et al*., 1999), northeastern Kansas's tallgrass prairie in northeastern Kansas (Quist *et al*. 2003; Althoff *et al*., 2009), and mixed grass prairie in southwestern Oklahoma (Leis *et al*., 2005).

Given the prevalence of grassland burning as both an intentional management practice and unintentional disturbance, and the role of fire on grassland health and species composition, the ability to detect burns over large areas is of interest to many people for not only prairie management, but also carbon cycle studies, air quality management, and habitat quality assessment (Bourgeau-Chavez *et al*., 1997; Towne and Owensby 1984; Dwyer *et al*., 2000; Huang *et al*., 2013; Raynor 2015). A frequent approach to burn detection uses remotely sensed data from active or passive remote sensing (Bourgeau-Chavez *et al*., 1997; Liu *et al*., 2014).

This study uses high spatial resolution satellite imagery from the Landsat 5 TM and Landsat 7 ETM+ sensors and a supervised classification technique developed by Mohler (2011) to detect burn scars over the period 2001-2011 to create a contemporary burn history of Smoky Hill ANGR and a nearby non-military Comparison Site. The frequency of burns between 2001-2011 is then compared between the two sites. The research question is:

- What is the spatial distribution of disturbances (burning) at Smoky Hill ANGR and do these differ significantly from adjacent non-military lands?

Study Areas

Smoky Hill Air National Guard Range (ANGR) is a 13,708 hectare (ha) range located southwest of Salina, Kansas in Saline and McPherson Counties (Figure 12). It has been in military use since 1942 when the site was known as Camp Phillips (1942-1944). Occupying the center of the range is a 4,091 ha Impact Area for air-to-ground bomb training (Busby *et al*., 2007). The site is situated in the Smoky Hills ecoregion of Kansas (Hansen 2012), a 2,028,997 ha transition area comprised of tallgrass prairie in the east to mixed grass prairie in the west

(Busby *et al*., 2007). Smoky Hill ANGR vegetation at present time is mostly Dakota Hills Tallgrass Prairie. The underlying geology is comprised of sandstone, shale, loamy colluvium (Hansen 2012). The climate at the range is temperate continental with large temperature swings. The average annual precipitation is 75.9 cm (Figure 4) and average temperature is 12.9ºC (NCDC 2013).

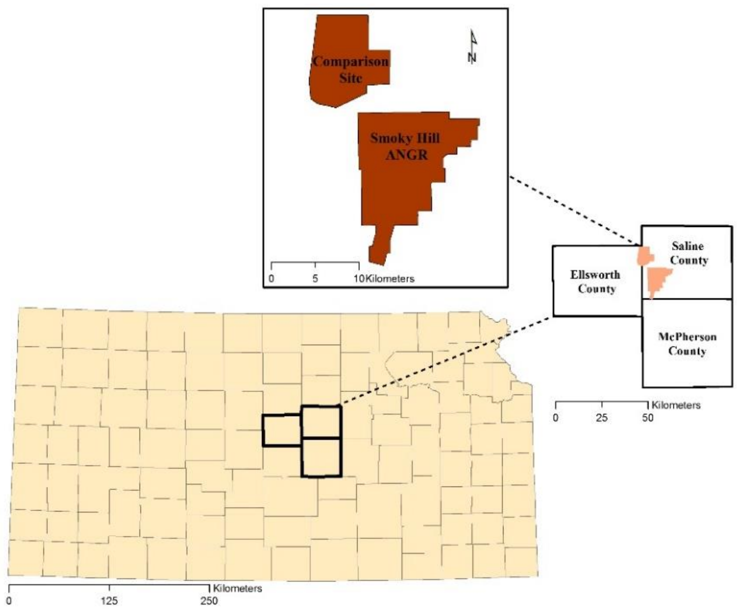

Figure 12 Study area map highlighting the location of the Smoky Hill Air National Guard Range (ANGR) and the Comparison Site used in this study.

The range is currently controlled by the 184th Bomb Group, Kansas Air National Guard (Pike 2011) and is the largest bombing range in the nation with over 100 tactical targets. Outside of the very active Impact Area, training intensity is moderate and is leased for agriculture production and livestock grazing (Busby *et al.*, 2007). Smoky Hill ANGR is used almost exclusively (estimated 90% of use) by the Kansas Air National Guard (KSANG). It also sees some use (estimated 10% of use) by the Kansas Army National Guard (KSARNG).

In compliance with DoD policy, an Integrated Natural Resource Management Plan (INRMP) has been implemented at Smoky Hill Air National Guard Range (ANGR) (Engineering-Environmental Management, Inc. 2007). The goals for natural resource management at Smoky Hill ANGR are “to enhance and maintain biological diversity within the Range boundaries, while assuring the successful accomplishment of the military mission. Management practices should minimize habitat fragmentation and promote the natural pattern and connectivity of habitats; protect rare and ecologically important species; maintain and mimic natural processes; and restore species, communities, and ecosystems (Busby *et al*., 2007)”.

A comparison site located approximately 16 km northwest of Smoky Hill ANGR was identified for this study. The Comparison Site is a 7,351 ha, large unbroken area of grassland used for grazing cattle, has very little cropland, and few houses or roads. It is in the same ecoregion as Smoky Hill ANGR and, due to its proximity to the military site, is assumed to have the same weather and climate conditions. Figure 13 shows the location of Smoky Hill ANGR and the Comparison Site with a background satellite image showing the proximity of the sites and similar landcover conditions.

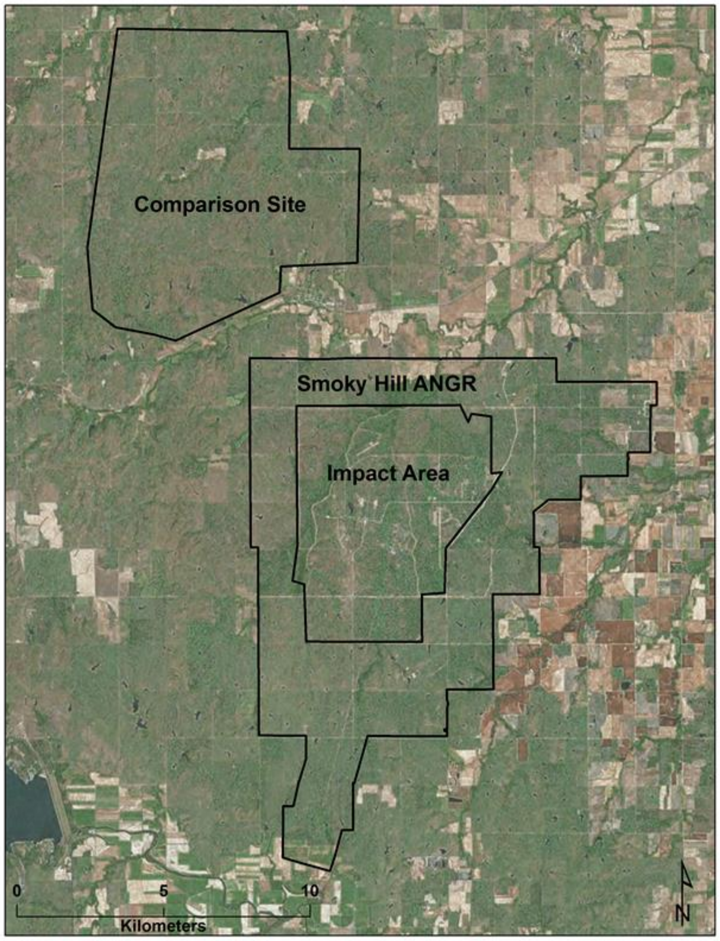

Figure 13 Detailed view of the Smoky Hill ANGR and Comparison Site. This image highlights the 4,091 ha Impact Area internal to Smoky Hill ANGR (image courtesy of the Environmental Systems Research Institute, Esri).

Data and Methods

Satellite Image Acquisition and Processing

The goal of this analysis is to determine whether or not each pixel was burned at least once during each year of the study. This result is then aggregated into a single composite heatmap image indicating the number of years in which a pixel burned over the period of 2001-2011. To accomplish this, Landsat 5 TM and Landsat 7 ETM+ imagery were downloaded from

EarthExplorer USGS website (http://earthexplorer.usgs.gov) at no cost. In total, 253 images spanning the 2001-2011 time period were downloaded. Each image was examined in ENVI 4.5 and checked for clouds or other issues that would have impacted the forthcoming burn scar classification. The objective of this preliminary examination was to identify a minimum of 1 image per month for the entire study period, or 132 total images, for the burn scar analysis. The goal for selecting the 1 monthly image was to capture the maximum burned area and make burns more easily detectable without the interference of vegetation regrowth. The selected representative monthly burn image ideally had the largest and freshest burn. Some months no usable images were available due to cloud contamination.

All images were then sorted into one of three categories: Burn Scar (Clear Image), No Burn Scar (Clear Image), and Cloudy. A total of 109 images were determined to be cloud-free while 23 were contaminated with clouds. Of the 109 usable images, 58 had visible burn scars (45 Landsat 5 TM and 13 Landsat 7 ETM+) that could be classified (Table 9). Images lacking visible burn scars were not used in the classification.

Month	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
January											
February											
March											
April											
May											
June											
July											
August											
September											
October											
November											
December											

Burn Scar and Clear Image	45	LS5
Burn Scar and Clear Image	13	LS7
No Burn Scar	51	
Cloudy Image	23	

Table 9 Inventory for Landsat 5 TM and Landsat 7ETM+ imagery used in the burn scar classification.

Since only 109 of the required 132 monthly images (83%) were usable in the analysis, gaps in the Landsat 5 TM/7 ETM+ image archive, use of MODIS Burned Area Monthly L3 Global 500m SIN Grid V005 images were investigated. The MODIS Burn Area images were downloaded from the NASA's Earth Observing System Data and Information System website (http://reverb.echo.nasa.gov/reverb) at no cost. To determine if the MODIS images were sensitive to the small scale and low intensity fires common in the study areas, three image dates were chosen when there were large burn scars known to be present (Figure 14). MODIS Burned Area Monthly images for these same time periods were downloaded and examined to see if fires were detected. None of the three MODIS Burned Area images detected fires during these times.

Since the MODIS Burned Area Monthly images weren't a suitable substitute for cloudy Landsat 5/7 images, gaps were left in the time series used for burn scar classification.

Supervised Image Classification

The 45 Landsat 5 TM and 13 Landsat 7 ETM+ images that had burn scars were calibrated within ENVI 4.5 prior to classification. Burn scar classification was also done within ENVI 4.5 using the "Scenario 7" technique reported by Mohler (2011) which featured a Minimum Distance Supervised Classification using the red and NIR bands from the Landsat 5/7 images. The resulting classified images had two classes for burned and unburned pixels. Though the technique appeared to excel at identifying burn scars, the initial classification also overestimated the burns by including densely forested areas and water features. To counter this, water and forest masks were created and the supervised classification was performed again (Table 10) (Mohler 2011). Once the classification was complete, images were exported from ENVI 4.5 as 8-bit TIF images with a spatial extent including both study areas. Classified image values were either 0 (no burn) or 1 (burn).

Mask Type	Spectral Band	Minimum Pixel Value	Maximum Pixel Value
Water	NIR	0	.14
Trees	NIR	0.31	0.4

Table 10 Characteristics of the forest and water masks used to improve the supervised classification of burn scars.

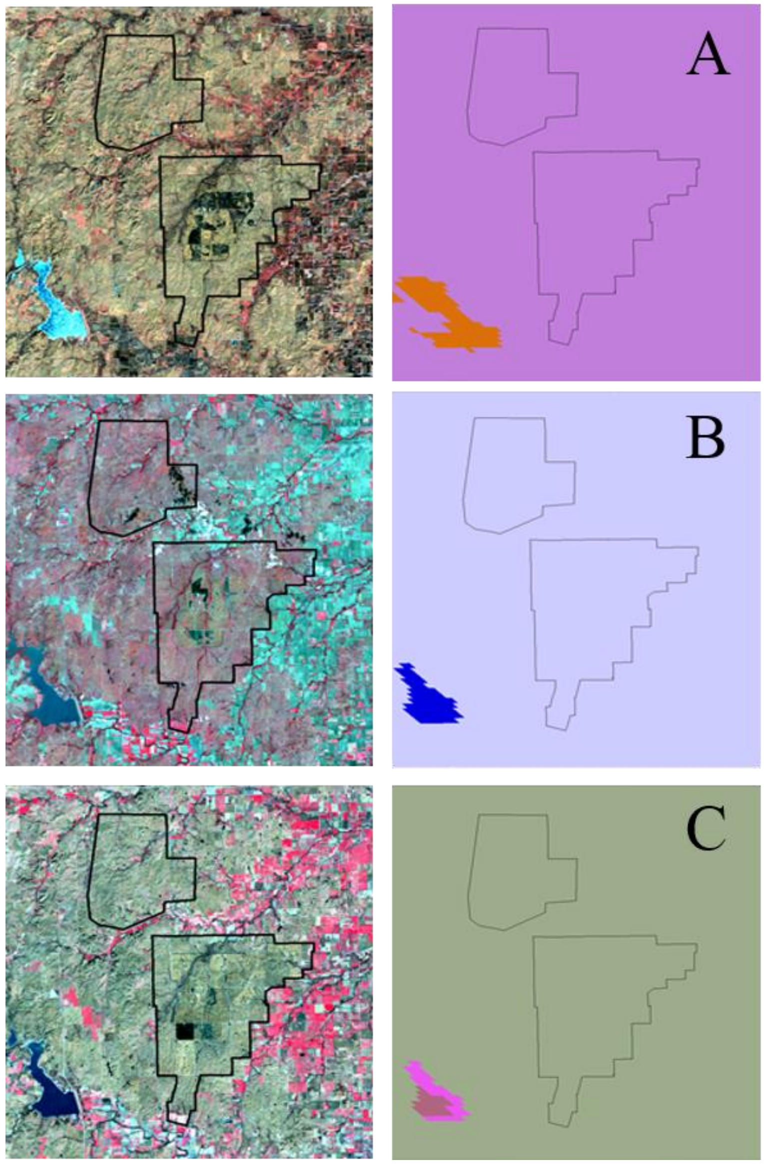

Figure 14 Visual validation of the MODIS Burned Area Monthly L3 Global 500 m SIN Grid V005 images (right) compared with Landsat 5 TM images (left) acquired during the same month. Images dates are 01/09/2001 for A, 09/14/2004 for B, and 12/01/2009 for C.

After classification, each monthly image in a year were combined in a GIS-based raster calculation to begin the estimation of the minimum annual burn frequency for 2001-2011. Each annual burn frequency image contained pixels with values ranging from 0 (no burns) to *n*, with *n* representing the maximum number of times a burn scar was detected on an annual basis. Once such images were generated for each year, they were reclassified so that each annual image contained a 0 (no burn scar) or 1 (burn scar regardless of the number of times it was detected). This reclassification step was necessary as a burn scar from the same fire event could have been detected across multiple image dates.

Next, a series of masks were created and applied to the reclassified images to prevent early winter burn scars from a previous year from also being counted in late winter the following year. Any burn scar detected from September to December would be used as a mask for the following January to March time period. Pixels that were burned anytime from September to December would not have enough time to regrow vegetation and be burnt again from January to March of the following year. Once the September to December masks were created and applied to the following year's burn history, the classified images were an appropriate estimate of minimum annual burn frequency. Finally, the minimum annual burn frequency images were combined in another GIS-based raster calculation. The result included pixel values ranging from 0-11.

Results

The estimated minimum burn frequency between 2001-2011 resulting from the supervised burn scar classification is shown in Figure 15. Visual analysis shows that burn scars, hence fire events, were more frequent at Smoky Hill ANGR than the Comparison Site. Considering only Smoky Hill ANGR, fires were more frequent inside the Impact Area than outside with approximately half of the Impact Area having burned 6 or more times.

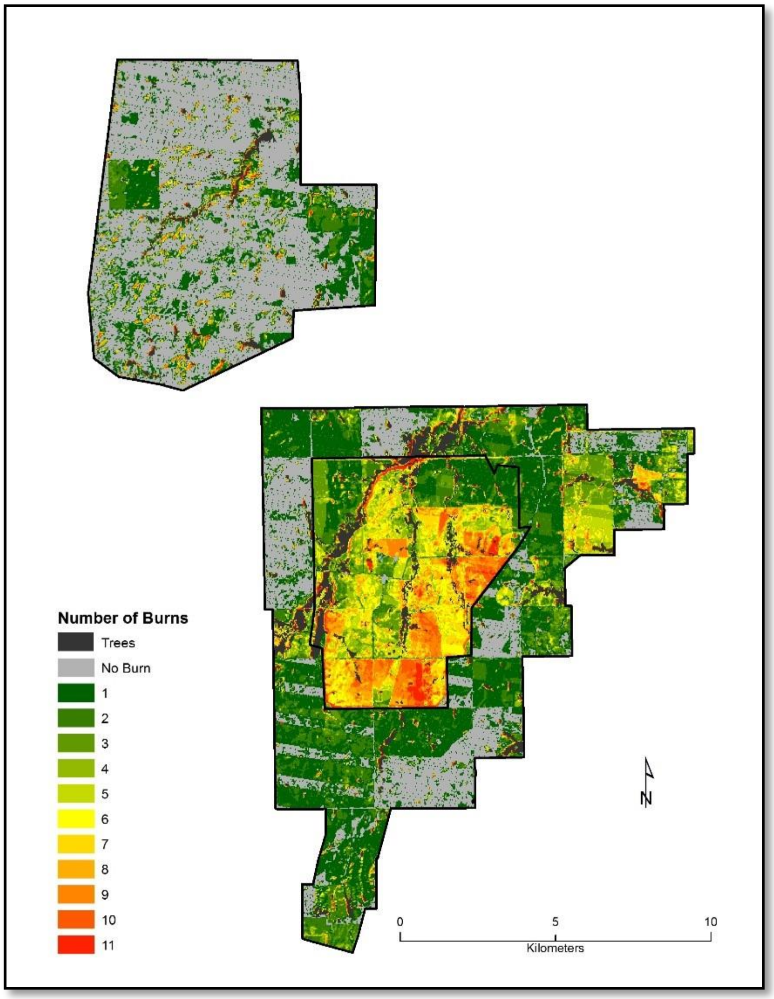

Figure 15 Estimated minimum burn frequency between 2001-2011 for Smoky Hill ANGR and Comparison Site.

Treating the Impact Area as a separate study area, only 9.2% of the area went unburned during the 11 year study period compared to 31.9% for Smoky Hill ARNG (excluding the Impact Area) and 67.3% of the Comparison Site (Table 11). The Impact Area shows a more even distribution of burn frequency values, while Smoky Hill ARNG (excluding the Impact Area) and the Comparison Site have right-skewed distributions with the most common minimum burn frequency values of 0-1 (Figure 16).

	Smokey Hill ANGR (excluding Impact Area)			Comparison Site			Impact Area		
No. Burns	No. Pixels	Area (ha)	Percent of Total Area (%)	No. Pixels	Area (ha)	Percent of Total Area (%)	No. Pixels	Area (ha)	Percent of Total Area (%)
0	32,951	2,965.6	31.92%	55,464	4,991.8	67.36%	4,660	419.4	9.23%
1	36,477	3,282.9	35.34%	15,801	1,422.1	19.19%	5,020	451.8	9.95%
2	15,082	1,357.4	14.61%	4,722	425.0	5.73%	3,786	340.7	7.50%
3	6,257	563.1	6.06%	1,657	149.1	2.01%	4,169	375.2	8.26%
4	3,801	342.1	3.68%	932	83.9	1.13%	4,021	361.9	7.97%
5	3,120	280.8	3.02%	724	65.2	0.88%	4,673	420.6	9.26%
6	1,734	156.1	1.68%	634	57.1	0.77%	5,520	496.8	10.94%
7	1,204	108.4	1.17%	600	54.0	0.73%	5,269	474.2	10.44%
8	870	78.3	0.84%	511	46.0	0.62%	4,393	395.4	8.71%
9	578	52.0	0.56%	568	51.1	0.69%	4,587	412.8	9.09%
10	485	43.7	0.47%	393	35.4	0.48%	2,941	264.7	5.83%
11	660	59.4	0.64%	334	30.1	0.41%	1,424	128.2	2.82%

Table 11 Summary of estimates for the minimum annual burning frequency between 2001-2011 for Smoky Hill ANGR (excluding the Impact Area), the Impact Area, and the Comparison Site.

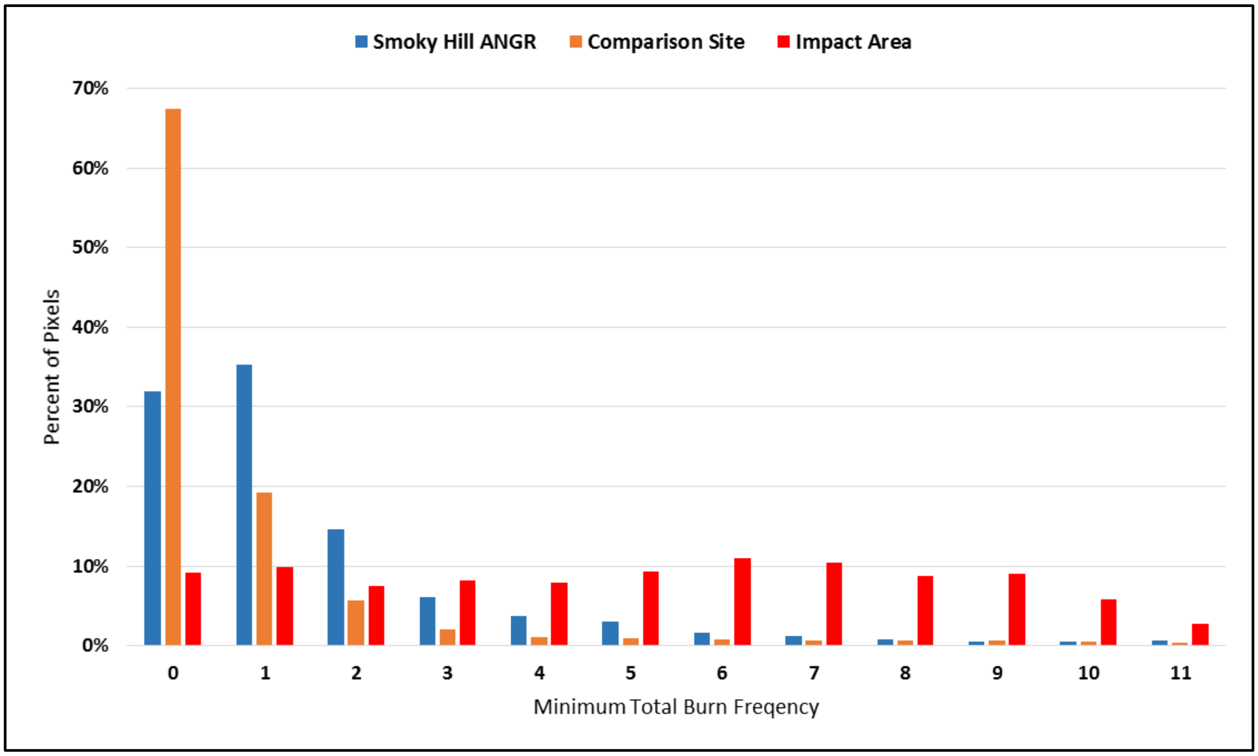

Figure 16 Histogram for minimum total burn frequency for the period 2001-2011 for Smoky Hill ANGR (excluding the Impact Area), Impact Area, and the Comparison site.

A Chi-squared contingency table analysis of minimum total burn frequency for the study period was performed comparing Smoky Hill ANGR (excluding the Impact Area), the Impact Area, and the Comparison Site. Results showed highly significant site-specific differences in the observed and expected frequencies [χ^2 (df = 22) = 152.36, p << 0.0001] suggesting the existence of a causal link between training activities within the Smoky Hill ANGR Impact Area and burn frequency.

Discussion and Conclusion

It is evident from visual inspection of Figure 15 that Smoky Hill ANGR is burned more frequently than the non-military Comparison Site and burning within Smoky Hill ANGR is mostly done within the Impact Area. Based on the Chi-squared contingency table analysis of minimum total burn frequency there is highly significant site-specific differences in the observed and expected frequencies at the study areas. The increased burning regime within the Impact Area is either caused by active training or purposeful burning to contain potential training induced fires.

There are visual signs of possible border burns in the minimum burn frequency image that show pixels that burned at least 11 times, once every year from 2001-2011 (Figure 17). Showing that there is intentional burn management happening within the Impact Area. Burning is a management technique widely used on tallgrass prairies (Vogl 1974; Towne and Owensby 1984; Herndon and Taylor 1986; Shay *et al*., 2001), so it would be normal for land managers at Smoky Hill ANGR to use it as such. Even if the burning is not being done for proper tallgrass prairie management it is a natural disturbance that is part of the grassland life cycle (Stewart 1951, Hulbert 1969).

It is known that military training affects the environment (Shaw *et al*., 1989; Wilson 1988; Quist *et al*., 2003; Whitecotton *et al*., 2000) and that those effects can have lasting impacts (Lathrop 1982). The increased burning at Smoky Hill ANGR and specifically within the Impact Area, caused by training activities or wildfire prevention, could be affecting the vegetation at the range. Based on this study it is known that the Comparison Site is burned less frequently than Smoky Hill ANGR and the Impact Area is burned most often. What is not known is if the burns are having an affect on the environmental conditions at the range. Further research needs to be done to determine if the increased burn disturbances at Smoky Hill ANGR are having different affects on the environment relative to the Comparison Site.

To create a more comprehensive burn history for Smoky Hill ANGR a couple things could be done. Landsat 5/7 image gaps could be filled in with other imagery to try and detect all burned pixels within a year. Also, creating a more granular dataset by counting all burns within a year and retaining the value, not just if it burned or not. To get a better understanding of how many times within a year areas are burned.

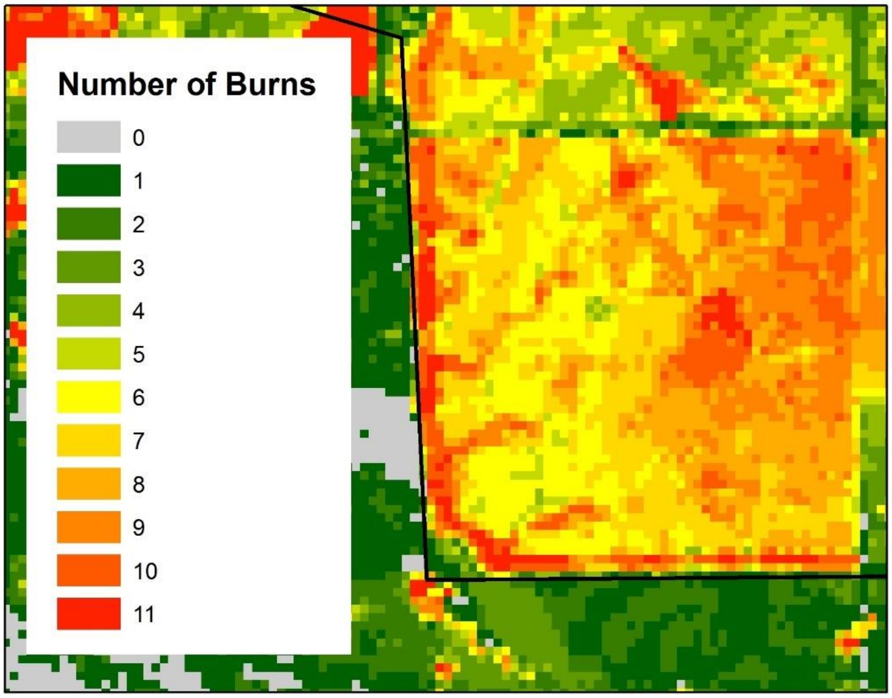

Figure 17 Close-up view of the southwest corner of the Impact Area within Smoky Hill ANGR showing the existence of a possible burned perimeter serving as a fire break.

Chapter 5 - Time Series Analysis of Long-term Vegetation Dynamics at Smoky Hill Air National Guard Range, Kansas using Moderate Resolution Satellite Imagery

Abstract

Military installations are import assets for the proper training of armed forces. To ensure the continued viability of the training grounds, management practices need to be implemented to sustain the necessary environmental conditions for safe and effective training. This study uses satellite imagery over an 11 year time period to gain insight into vegetation conditions over a military installation in Kansas. The study areas are Smoky Hill Air National Guard Range (ANGR), Impact Area (within the range), and a non-military Comparison Site. MODIS imagery was collected 23 times a year from 2001-2011 resulting in 253 images. NDVI was extracted and analyzed within "R" using the statistical package BFAST. Vegetation trends and disturbances were gathered from the BFAST analysis for all three study areas. It was found that the overall trend for all three study areas was mostly positive, there were more disturbances within the Impact Area, and the largest disturbances within the Impact Area responded negatively. Comparisons were made between this study and a BFAST analysis of another military installation and it was found that both military installments are different than their respective reference sites. It was also found that the difference in training between the sites is having an effect in overall trend response. It was concluded that the training at Smoky Hill ANGR is disturbing the vegetation but does not seem to be having a negative effect on the overall long-term vegetation condition.

Introduction

Sustainable use of military training grounds is a necessity for the continued viability of the installations for training. The land that the U.S. military trains on is an invaluable asset that helps our troops stay in top shape for war time actions. The Department of Defense (DoD) controls 7,859,618 hectares (ha) of land within the United States (Gorte *et al*., 2012). Training activities on these 7+ million ha can have dramatic impacts on the environment (Shaw *et al*., 1989).

The Integrated Natural Resource Management Plan (INRMP) was implemented at Smoky Hill Air National Guard Range (ANGR) because of DoD policy (Engineering-environmental Management, Inc. 2007). INRMP implements ecosystem management within military mission requirements (Busby *et al*., 2007, p. 3). In 2002, Smoky Hill ANGR asked the Kansas Biological Survey (KBS), at the University of Kansas, to do an inventory of the flora and fauna over the entire range and to rate the overall ecological condition at the range (Busdy *et al*., 2007).

The KBS concluded that Smoky Hill ANGR is an example of a large preserved tallgrass prairie with large spans of unbroken prairie that serve as a hotspot for biodiversity for the Great Plains. Overall the KBS categorized the grassland communities at Smoky Hill ANGR as “good” because of their thoughtful management practices. A goal for the INRMP is to raise the overall quality from “good” to “excellent” (Busby *et al*., 2007).

All of the surveys and analysis that the KBS did at Smoky Hill ANGR were extremely time intensive. They gathered immense amounts of data about the range for baseline numbers for the management to use in further developing the tallgrass prairie at the range. INRMP now has quantitative numbers to compare future environmental surveys to.

A tool that INRMP at Smoky Hill ANGR could add to their management program, along with their baseline information of species composition from the KBS, is a time series analysis of vegetation conditions for the entire range. INRMP knows what grass species are at the range from the KBS, but they don't know the trajectory of vegetation trends or the number, magnitude, and location of disturbances (*i.e.,* breaks in trend) over the entire range.

The purpose of this study is to use the statistical package Breaks For Additive Seasonal and Trend (BFAST), within the statistical software program "R", to generate a time series trend and disturbance analysis of the vegetation conditions at Smoky Hill ANGR. My research questions are:

- What is the frequency and spatial distribution of significant disturbances at Smoky Hill ANGR and do these differ significantly from adjacent non-military lands?
- What is the long-term interannual trend in vegetation conditions, as inferred using normalized difference vegetation index (NDVI) data, at Smoky Hill ARNG and do estimated trends differ significantly from adjacent non-military lands?

Background and Objectives

Monitoring vegetation cover and condition is a necessary process for understanding many phenomena including terrestrial primary productivity, concentrations of atmospheric CO_2, the hydrologic cycle, and others. Monitoring vegetation cover and condition once was done mostly in the field by surveying an area of interest. This can be a very cumbersome process or nearly impossible if the study area is extremely large. An answer to the problem of monitoring large areas without *in-situ* surveys is remote sensing (Tucker *et al*., 1985; Cihlar *et al*., 1991).

Ecosystems need to be monitored over time and land surface data needs to be gathered for proper management (Coppin *et al*., 2004). Being able to use remotely sensed data can improve environmental management practices by providing timely data over large areas (Underwood 2006). Using remotely sensed images a time series analysis can reveal NDVI values that can provide indicators about the condition of vegetation.

Normalized difference vegetation index (NDVI) is a vegetation condition metric that can be derived from satellite imagery to provide information about vegetation and vegetation change (Wright *et al.*, 2012). NDVI has been shown to correlate with leaf-area index (LAI), percent cover, and aboveground biomass (Cihlar *et al*., 1991). It has also been suggested that NDVI relates to photosynthesis and transpiration (Running 1988). Knowing NDVI values for an area over a long time period can produce valuable information about vegetation conditions.

For my study I will be using 250m 16-day composite Moderate Resolution Imaging Spectroradiometer (MODIS) imagery that is on board the Terra satellite, a program within the Earth Observing System (EOS). The EOS program is intended for studying the role of vegetation in large-scale processes and for understanding how Earth functions as a system (Huete *et al.,* 2002, p. 195).

Many tools have been developed to extract valuable information from satellite imagery. One of these tools is Breaks of Additive Seasonal and Trend (BFAST). BFAST is a generic change detection statistical model for time series analysis that is relatively new. BFAST is able to discriminate seasonal phenological changes while still calculating long-term change. BFAST works on a per-pixel basis and will breakdown a time series into trend, seasonalitly, and noise components without having to set thresholds, choose time frames, or define a change trajectory

(Verbesselt *et al*., 2010a, p. 107). Four characteristics make BFAST appropriate for near real-time global scale disturbance detection (Verbesselt *et al.*, 2012, p. 106):

- Has a low processing time
- Does not require definition of thresholds
- Can perform with data gaps
- Analyzes full temporal detail of a time series

Study Areas

Smoky Hill Air National Guard Range (ANGR) is a 13,708 hectare (ha) range located southwest of Salina, Kansas in Saline and McPherson Counties (Figure 18). It has been in military use since 1942 when the site was known as Camp Phillips (1942-1944). Occupying the center of the range is a 4,091 ha Impact Area for air-to-ground bomb training (Busby *et al*., 2007). The site is situated in the Smoky Hills ecoregion of Kansas (Hansen 2012), a 2,028,997 ha transition area comprised of tallgrass prairie in the east to mixed grass prairie in the west (Busby *et al*., 2007). Smoky Hill ANGR vegetation at present time is mostly Dakota Hills Tallgrass Prairie. The underlying geology is comprised of sandstone, shale, loamy colluvium (Hansen 2012). The climate at the range is temperate continental with large temperature swings. The average annual precipitation is 75.9 cm (Figure 4) and average temperature is 12.9ºC (NCDC 2013).

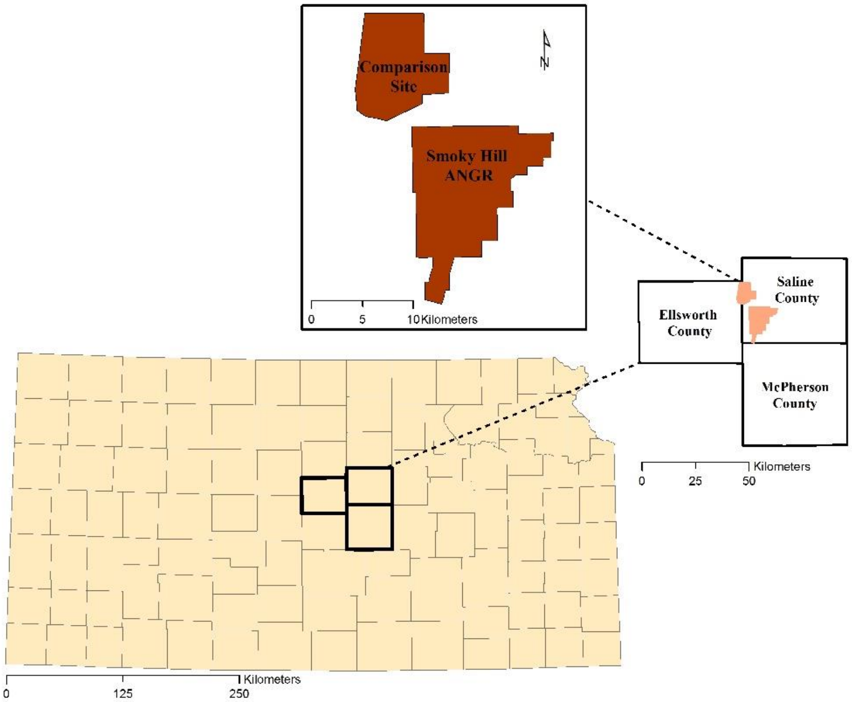

Figure 18 Study area map highlighting the location of the Smoky Hill Air National Guard Range (ANGR) and the Comparison Site used in this study

The range is currently controlled by the 184th Bomb Group, Kansas Air National Guard (Pike 2011) and is the largest bombing range in the nation with over 100 tactical targets. Outside of the very active Impact Area, training intensity is moderate and is leased for agriculture production and livestock grazing (Busby *et al.*, 2007). Smoky Hill ANGR is used almost exclusively (estimated 90% of use) by the Kansas Air National Guard (KSANG). It also sees some use (estimated 10% of use) by the Kansas Army National Guard (KSARNG).

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Management practices should minimize habitat fragmentation and promote the natural pattern and connectivity of habitats; protect rare and ecologically important species; maintain and mimic natural processes; and restore species, communities, and ecosystems (Busby *et al*., 2007)".

A comparison site located approximately 16 km northwest of Smoky Hill ANGR was identified for this study. The Comparison Site is a 7,351 ha, large unbroken area of grassland used for grazing cattle, has very little cropland, and few houses or roads. It is in the same ecoregion as Smoky Hill ANGR and, due to its proximity to the military site, is assumed to have the same weather and climate conditions. Figure 19 shows the location of Smoky Hill ANGR and the Comparison Site with a background satellite image showing the proximity of the sites and similar landcover conditions.

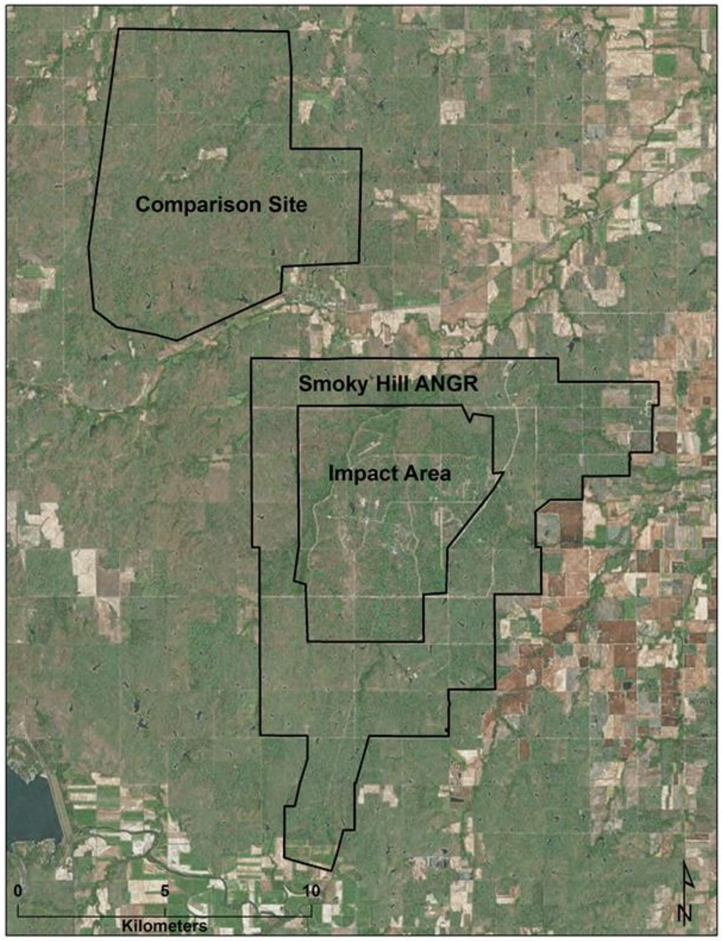

Figure 19 Detailed view of the Smoky Hill ANGR and Comparison Site. This image highlights the 4,091 ha Impact Area internal to Smoky Hill ANGR (image courtesy of the Environmental Systems Research Institute, Esri).

Data and Methods

MODIS Image Acquisition and Processing

The imagery analyzed was 16-day maximum value composite normalized difference vegetation index (NDVI) images (250 meter spatial resolution) recorded by the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard the Terra satellite (Maccherone 2012). The MODIS sensor flies over Smoky Hill ANG and the Comparison Site every day and captures an image. To make a 16-day maximum value composite, a total of 16 consecutive daily images are combined into the composite which contains the maximum value recorded during the period for each pixel. A total of 23 MODIS composite images are produced each year. For this study, satellite data collected during the period 2001-2011 was acquired, yielding a total of 253 individual composite images. Satellite images from MODIS were gathered from the National Aeronautics and Space Administration Earth Observing System Data and Information System website (http:// http://reverb.echo.nasa.gov) at no cost. Raw images, from the website, are comprised of two separate files, including a .hdf (image) file and a .xml (text) file.

The raw MODIS imagery downloaded from NASA, containing the study areas, is in sinusoidal projection and covers nearly half of the eastern United States. The MODIS imagery was reprojected into NAD 1983 UTM Zone 14N and clipped down to cover most of Kansas. In addition, the NDVI band is extracted from the multiband .hdf file. All of this preprocessing is automated within ENVI 4.5 using an Interactive Data Language (IDL) script.

Boundary shapefiles for the Comparison Site and Smoky Hill ANGR where constructed using ArcMap 10.0 based on source data from Open Street View. The Smoky Hill ANGR boundary was checked for accuracy by looking at the boundary maps that the KBS report produced on Smoky Hill ANGR and cross checking the boundary with the one produced in ArcMap.

BFAST Processing

Time series analysis was performed on the MODIS NDVI images for the study areas using the BFAST routine available with the “R” statistical environment. BFAST is a time series analysis technique that will run data gaps, doesn’t require thresholds to be set, and it can handle large datasets (Lu *et al*., 2001; Johnson *et al*., 2008; Verbesselt *et al*., 2010a). LOESS-driven

STL temporal decomposition is the temporal decomposition that BFAST is based on that was first developed by Cleveland and Delvin (1988) then modified by Verbesselt *et al*., (2010) to create BFAST.

BFAST is a time series analysis tool that uses an additive model to decompose the raw NDVI data into seasonal trend, long-term trend (and breaks in the trend), and noise for each pixel. The additive model is (Hutchinson *et al*., 2015):

$$Y_t = C_t + S_t + \varepsilon_t$$

Equation 2 Additive Model Equation Used in BFAST

C_t = trend

S_t = seasonal

ε_t = residuals

Before BFAST will estimate trend and seasonal components, it performs a test that looks for abrupt differences in the data using ordinary least squares residuals (Zeileis and Kleiber 2005). If a significant difference is found the number of breaks in trend and their location are determined using the method outline from Bai and Perron (2009).

For BFAST to run within "R", the following library programs must be loaded:

1. zoo- S3 Infrastructure for Regular and Irregular Time Series (Z's ordered observations)
2. sandwich- Robust Covariance Matrix Estimators (Depends on zoo)
3. MASS- Support Functions and Datasets for Venables and Ripley's MASS
4. quadprog- Functions to solve Quadratic Programming Problems
5. tseries- Time series analysis and computational finance (Depends on quadprog and zoo)
6. strucchange- Testing, Monitoring, and Dating Structural Changes (Depends on zoo and sandwich)
7. fracidiff- Fractionally differenced ARIMA aka ARFIMA (p, d, q) models

8. iterators- Iterator construct for R

9. codetools- Code Analysis Tools for R

10. foreach- Foreach looping construct for R (Imports iterators)

11. bfast- Breaks For Additive Season and Trend

*All of the information about the "R" packages is from CRAN Packages By Name- The Comprehensive R Archive Network. HYPERLINK "http://cran.r-project.org/web/packages/available_packages_by_name.html" http://cran.r-project.org/web/packages/available_packages_by_name.html.

Before the BFAST script is run 5 parameters must be set (Table 12): length of the time series represented by the total number of images available, length of the season or the number encompassing the complete vegetation cycle, the season model, a value (h) corresponding to the minimum time interval between potential breakpoints in the seasonal or trend components or the number of images in one vegetation cycle divided by the total number of images in the time series, and the maximum number of break points.

5 BFAST Parameters	
Total Number of Images	253
Images for Vegetation Cycle	16
Season Model	Harmonic
Minimum Time Interval	0.1
Maximum Number of Breakpoints	11

Table 12 The 5 parameters set for BFAST to run on the three study areas.

Once the parameters are set, the BFAST script pulls in a comma separated values (.csv) file containing NDVI values for each pixel (rows) for all composite periods (columns, n=253). A BFAST analysis is run on every pixel within the study areas and generates seasonal, trend, and noise components for each pixel (Figure 20). The BFAST results are then used for further analysis and mapping. Maps generated from the BFAST results are trend over time, amount and location of breaks, and vegetation response to the largest break in trend.

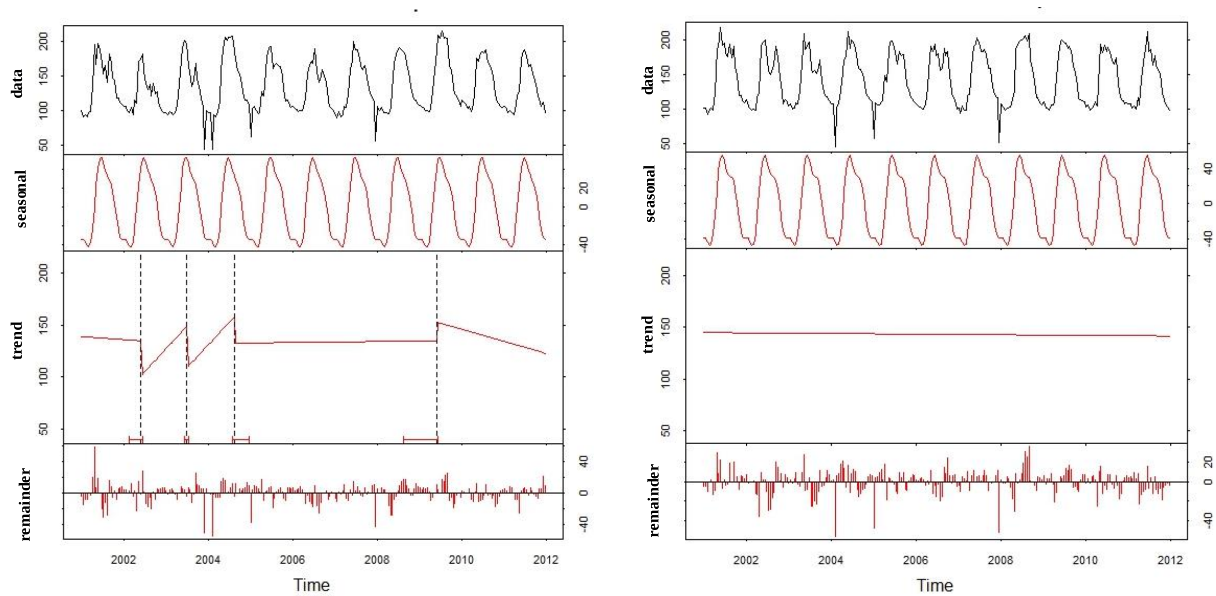

Figure 20 Raw 16-day MODIS NDVI time series between 2001-2011 (black) and components resulting from BFAST temporal decomposition (red) for two grassland pixels within the Impact Area. The graph on the left shows an overall negative trend, 4 breaks in trend, and an abrupt decrease in greenness at the largest magnitude break. The graph on the right illustrates a stable (slope not different from null) with no significant breaks.

Statistical Analysis of Long-Term Trends

After BFAST runs it will produce two different indicators for trend. The first one represents the slope of the trend over the entire 11 year time series from 2001-2011. It looks solely at the overall slope of the trend line. A Student t-test (Equation 3) was run on the slope of every trend line for every pixel to see if there was a slope significantly different from null.

$$t = (a_n - a_0)/(\frac{\sqrt{\left(\frac{1}{n-1}\right)\sum(x-\bar{x})^2}}{\sqrt{n-3}})$$

Equation 3 Student t-test

a_n = slope of the trend

a_0 = slope of a null trend (0)

n = number of images into the time series

x = time series NDVI value

$\bar{x}$ = mean NDVI value of the time series

Depending on the statistical significance and direction of the sign of the slope, all of the pixels were divided up into three categories to then be mapped and analyzed (Table 13).

Trend Class	Significance of Trend Slope Value (**?** = 0.05)	Sign of Trend Slope	Interpretation	
			NDVI Change	Vegetation Condition
Negative	Slope value significantly different from a null slope	Negative	Decrease	Decline
Positive		Positive	Increase	Improve
Stable	Slope value not significantly different from a null slope	Negative and Positive	Stable	No change

Table 13 Three categories for interpreting the trend results.

Long-Term Interannual (Gradual) Trend Validation

One of the goals of the overall study is to test the effectiveness of the BFAST time series analysis tool in tracking vegetation trends and disturbances using low-resolution satellite imagery. An approach to validating this technique is to compare the trend results from BFAST with those from an alternative method. One method, recommended by Borak *et al*., (2000), has proven well adapted for grassland ecosystems (Serneels *et al*., 2001; Jacquin 2010; Hutchinson *et al*., 2015). This method only requires two high-spatial resolution (HSR) NDVI images acquired near the beginning and end of the study period. The main advantages of this method compared to post-classification change analysis is that field data is not required and interpretation of NDVI change is easier than changes in landcover classes. The four steps below were taken to perform this validation method (Hutchinson *et al*., 2015, p. 360):

- Step 1: Two Landsat-5 images from 06/18/2001 and 06/30/2011 were acquired from the USGS Global Visualization Viewer website (http://glovis.usgs.gov) and were processed to derive the NDVI.
- Step 2: The difference in NDVI (2011-2001) was calculated for all pixels and the mean and standard deviation of the NDVI difference were computed for each site. Three classes were created (browning, no change, greening) based on a threshold (±0.5 standard deviations of mean NDVI difference).
- Step 3: The Landsat NDVI change classes were then resampled to the same spatial resolution of the MODIS imagery using a 250 m x 250 m grid. In order to assign a single change class to the down-sampled image, the percentage area of each Landsat change class was first calculated for each cell of the grid. A minimum threshold of 70% area for a single change class was then used to determine whether or not each cell would be retained for analysis or discarded.
- Step 4: A confusion matrix was constructed with rows representing the resampled Landsat change classes and columns the MODIS change classes, with the Landsat change classes serving as the reference. Figures on the diagonal indicate class-by-class agreement.

Magnitude, Direction, and Number of Significant Breaks in Trend

The second trend indicator was dramatic change in vegetation condition as found by breaks in the trend, there was a significant change in NDVI values from one image to the next. BFAST will not only detect the number of breaks but also the magnitude of the biggest break and its sign (positive or negative). The magnitude and sign can give insight into post-disturbance vegetation response. All of the pixels where divided into three categories depending on their breaks (Table 14).

Break Class	Number of Breakpoints	Sign of Highest Magnitude of Change	Interpretation
No Break	0	N/A	No significant disturbances detected
Post-Disturbance Positive	1 or more	Positive	Significant disturbances detected and gradual improvement in condition
Post-Disturbance Negative	1 or more	-/+	Significant disturbances detected and gradual decline in condition

Table 14 Summary of the magnitude of the largest break for the study areas.

Limitations of BFAST

There are limitations to BFAST to consider when interpreting the output results. Some problems with how BFAST works are inherent to using composite imagery and some are based on how BFAST calculates results. When using MODIS 16-day maximum value composite NDVI imagery there could be values recorded for the maximum NDVI anywhere from 1 day to 31 days apart. The value analyzed by BFAST isn't recorded at equal time intervals and depending on season and disturbance activity this could result in missing disturbances all together or misinterpreting disturbance events.

Another limitation of BFAST is how trend is calculated. The overall trend of the time series is heavily influenced by the first and last NDVI image value. This meaning that if the first or last image is representing an abnormal year, drought or wet period, this could overly influence the overall trend and skew the trend to be positive or negative.

Image Quality Assessment

Because cloud contamination, snow cover, and aerosols in the atmosphere can lower the quality of the VI estimate measured by sensors such as MODIS, Huete et al. (2002) and Hutchinson et al. (2015) developed the constrained view angle-maximum NDVI value (CV-MVC) compositing technique. This method, which is used in the MOD13Q1 image product, reduces atmospheric and cloud effects in the final maximum value composite images. However, image contamination is still possible.

In order to assess the quality of the MODIS NDVI images, the pixel reliability band of the MOD13Q1 product was used. In this study, pixel reliability were used as described in NASA LP DAAC (2013) guidance to monitor NDVI quality. The purpose of VI quality analysis is assess the overall quality of the NDVI images and to identify areas suffering from persistent quality issues that might impact later analysis of long-term NDVI trends.

The pixel reliability band (11) from the MOD13Q1 HDF file for each image date in the 2001-2011 time series was extracted, clipped to the extent of the study area, and re-projected to NAD 83 UTM Zone 14N. Pixel reliability values (Table 15) for the entire time period were then quantified to determine their percentage membership into each reliability rank category.
Based on pixel reliability rank (Table 15), the vast majority of study area pixels were rated as good quality throughout the study period (Figure 21).

Pixel Reliability Rank	Classification	Description	Minimum %	Maximum %
-1	Fill/No data	Not processed	0.0	0.0
0	Good data	Use with confidence	93.2	98.4
1	Marginal data	Useful but look at other QA information	0.4	3.9
2	Snow/Ice	Target covered with snow/ice	1.2	3.6
3	Cloudy	Target not visible, covered with cloud	0.0	0.4
4	Estimated	Based on MODIS historic time-series. All products are gap-filled, indicating whether or not the value was interpolated from long-term averages.	0.0	0.0

Table 15 MODIS MOD13Q1 pixel reliability ranks, their interpretation, and summary of reliability values for study area pixels between 2001-2011 (adapted from NASA LP DAAC, 2013)

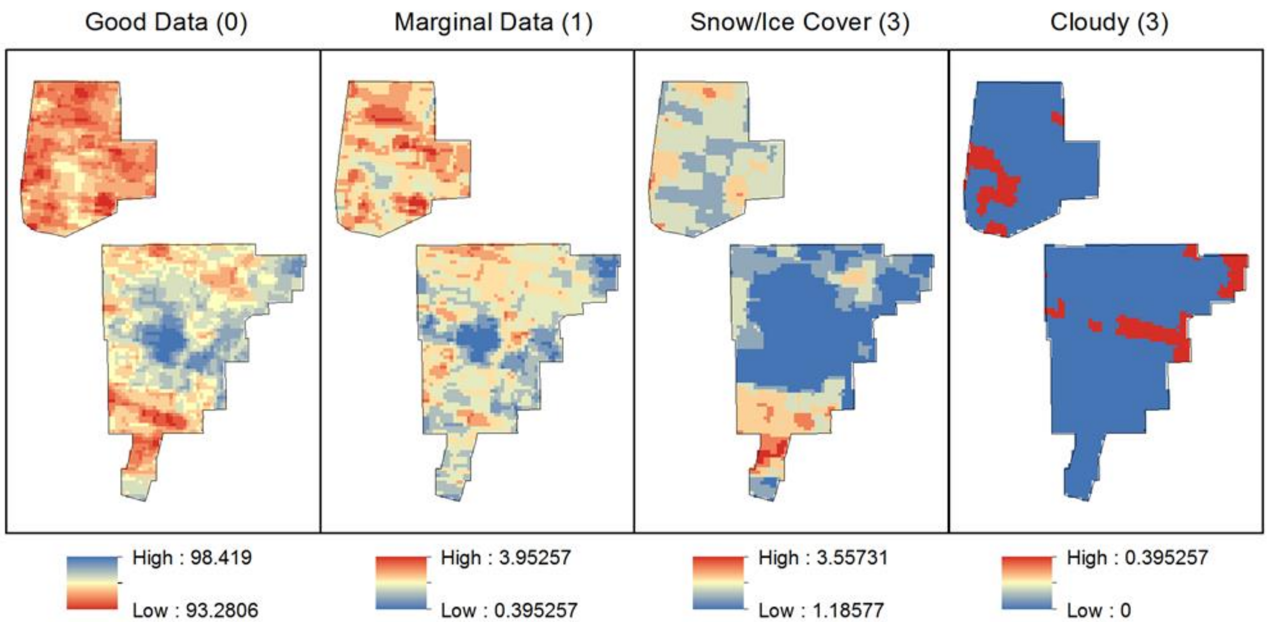

Figure 21 Maps of MODIS MOD13Q1 reliability values for study area pixels between 2001-2011.

Results

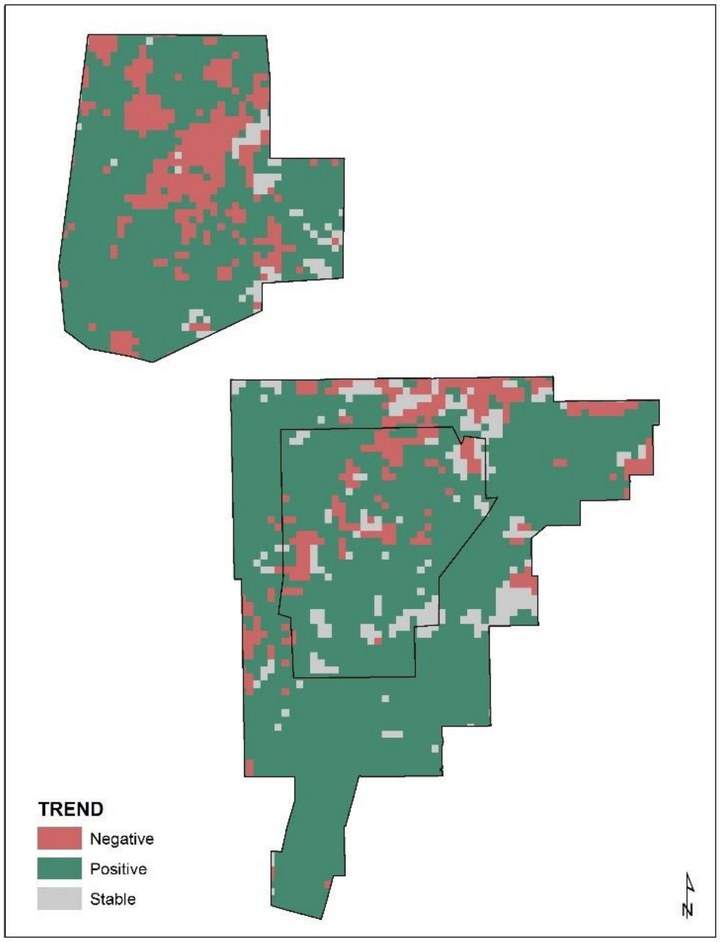

Figure 22 Map of the vegetation trends from 2001-2011 at the study areas. Green represents a positive (greening) trend and red represents a negative (browning) trend

Long-Term Trends

Analysis of the BFAST results show that a majority of the pixels for the Comparison Site, Smoky Hill ANGR, and the Impact Area are trending positive, showing an increase in greenness (Figure 22). Pixels that show a statistically significant (α = 5%) positive slope are represented as green, pixels that show a statistically significant (α = 5%) negative slope shown in light red, and stable pixels are shown in gray. This map allows for Smokey Hill’s land management team to access the vegetation trends across the whole range for the overall long-term vegetation conditions from 2001-2011. Areas in green represent an improvement in vegetation health, a greening up of vegetation over those 11 years and the light red represent a decrease in vegetation health, a browning in the vegetation and the stable vegetation is gray.

Looking at Smoky Hill ANGR (excluding the Impact Area) and the Impact Area the overall trends are very similar with the Comparison Site being slightly more varied. All three sites have 70%+ of their pixels greening up over the 11 year time frame (Table 16). A Chi-squared contingency table analysis was run to determine if the overall trend from study area to study area were different. The results show no significant site-specific difference in the observed and expected frequencies [χ^2 (df = 4) = 7.07, p > 0.1] meaning that the trends observed are independent of study area.

Overall Trend	No. Pixels	Area (ha)	Percent of Total Area (%) Negative	No. Pixels	Area (ha)	Percent of Total Area (%) Positive	No. Pixels	Area (ha)	Percent of Total Area (%) Stable
Comparison Site	337	1,798	23.02%	1,046	5,582	71.45%	81	432	5.53%
Smoky Hill ANGR	216	1,153	11.92%	1,432	7,641	79.03%	164	875	9.05%
Impact Area	112	598	12.31%	700	3,735	76.92%	98	523	10.77%

Table 16 Summary of the overall trend results at the study areas.

Validation of Long-Term Trend Results

Evaluation of the confusion matrix provides one form of validation of the BFAST-derived MODIS trend classes at Smoky Hill and the Comparison Site (Table 17). For both sites, producer's accuracy (number of correctly estimated pixels divided by the column total for a trend class) was highest for the positive and lowest for the negative trend class. At Smoky Hill, both the HSR-derived negative and positive change classes were confused with the BFAST stable class. At the Comparison Site, there was important, but less, disagreement between the HSR and BFAST negative trends classes. However, the HSR positive trend class was often confused with the BFAST negative and stable classes.

In this study, we were most interested in the negative trend class to highlight potential areas of degradation for land managers. Unfortunately, these validation results provide little confidence in the accurate interpretation of both the BFAST negative and positive trend classes. The 2011 image was acquired nearly two weeks later (June 30) than that used in 2001 (June 18). During June in both years, study site vegetation was at, or near peak development. However, warmer temperatures in 2011 likely supported advanced vegetation growth that, when compared with NDVI from 2001, resulted in a lower range and less variability in NDVI differences than was expected. When classifying the Landsat NDVI difference image using the standard deviation approach, more data values then fell into the ‘no change’ class. In addition, visual examination of the HSR images show evidence of several disturbances yielding positive and negative differences that would be masked by the smoothing performed in BFAST. These results confirm some of the limitations of using this established validation approach and highlight challenges remaining with the validation of trend analysis results derived from medium spatial resolution satellite data.

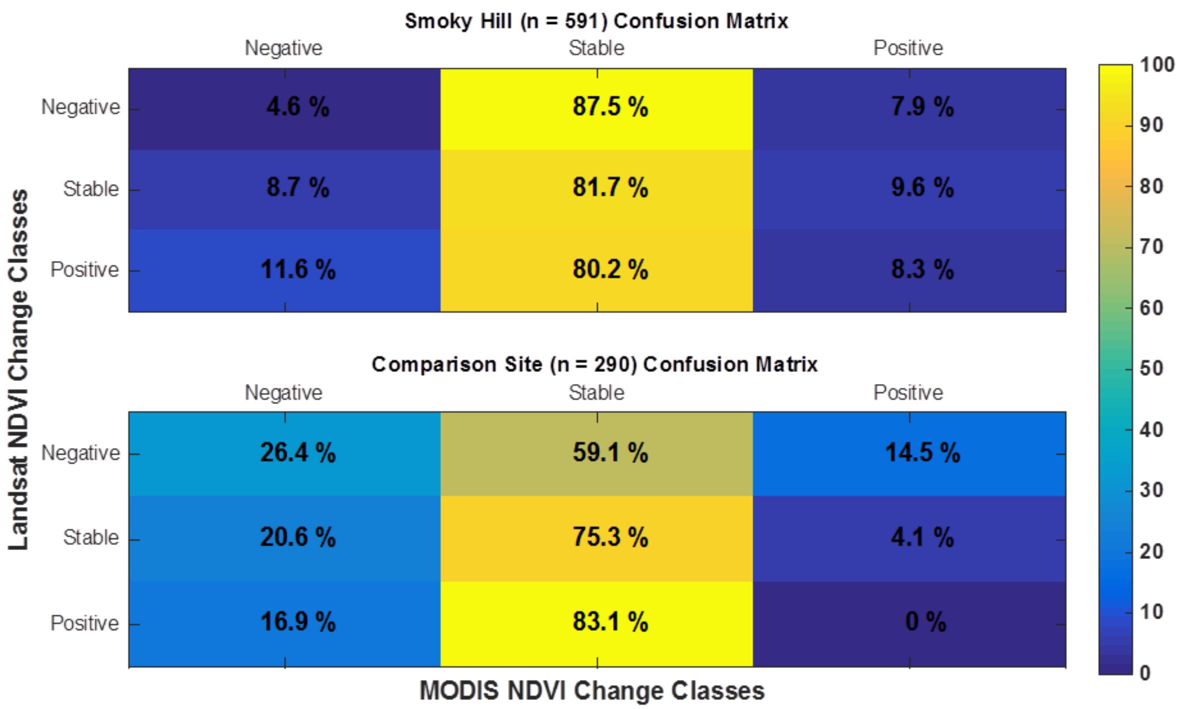

Table 17 Confusion matrix with validation results for BFAST-derived MODIS trend classes. Landsat NDVI change classes are considered the reference. Numbers are the percentage of MODIS pixels belonging to the each Landsat class.

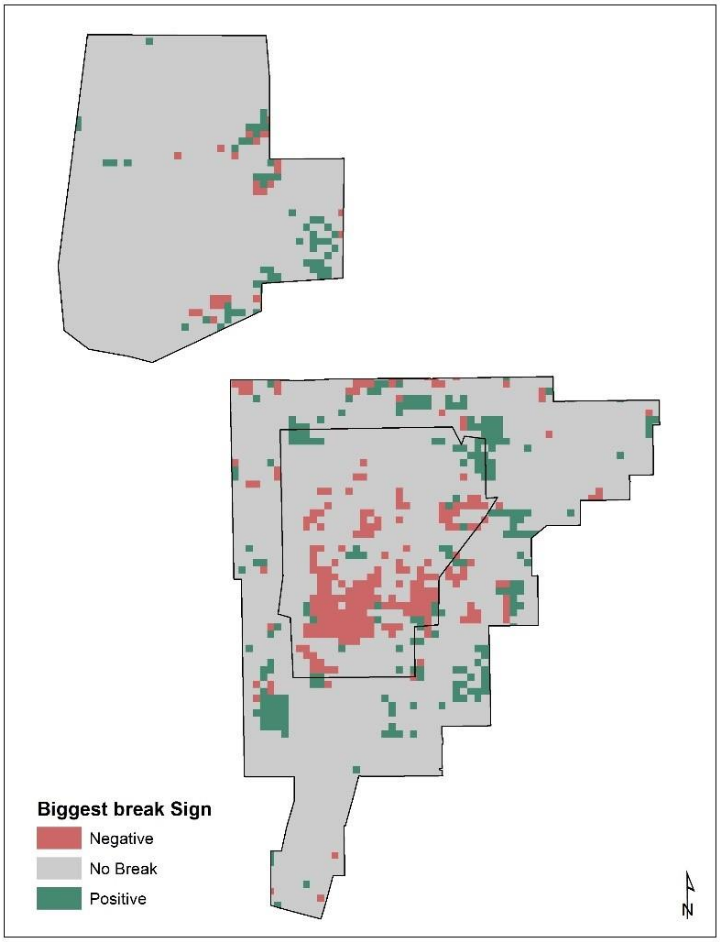

Figure 23 Map of the sign (+/-) of the largest magnitude break.

Magnitude and Direction of Breaks in Trend

The next aspect of the BFAST analysis is looking at an abrupt change from the trend, and disturbance. These disturbances in the trend can either have a negative (browning) or a positive (greening) response from the vegetation. These responses can start to give you an idea of what type of disturbances caused a break in trend (Figure 23).

In the Impact Area 76.5% of the largest disturbance responses caused browning compared to Smoky Hill ANGR (excluding the Impact Area) and the Comparison Site with 30% (Table 18). Smoky Hill ANGR (excluding the Impact Area) and the Comparison Site have the same percent of pixels responding to disturbances 70% greening and 30% browning. A Chi-squared contingency table analysis was run on the response to the largest break. Results showed highly significant site-specific difference in the observed and expected frequencies [χ^2 (df = 2) = 59.35, $p << 0.0001$] meaning that the responses to the largest break are dependent on study area.

Sign of the Magnitude of the Largest Break	No. Pixels	Area (ha)	Largest Break Negative (%)	No. Pixels	Area (ha)	Largest Break Positive (%)
Comparison Site	27	144	29.67%	64	342	70.33%
Smoky Hill ANGR	77	411	30.20%	178	950	69.80%
Impact Area	186	993	76.54%	57	304	23.46%

Table 18 Summary of the sign (+/-) of the largest break at the study areas.

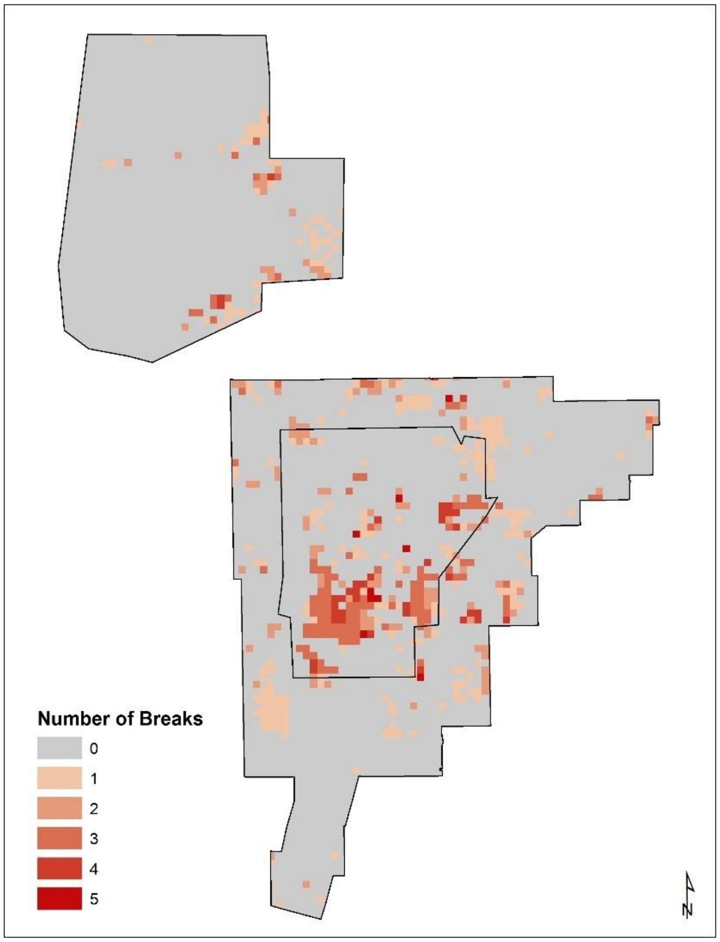

Figure 24 Map of the total number of breaks within the study areas from 2001-2011.

Number of Breaks in Trend

The last aspect analyzed with BFAST was the number of breaks from the trend. This shows how many disturbances occurred that caused a negative (browning) or positive (greening) response in the vegetation.

The area with the largest percentage of pixels having at-least one break is the Impact Area with 26.7%. Smoky Hill ANGR (excluding the Impact Area) has 14.07% with at-least one break and the Comparison Site has only 6.22% with at-least one break (Table 19). A Chi-squared contingency table analysis was run to determine if there was a statistical difference between the number of breaks at the study areas. Results showed significant site-specific differences in the observed and expected frequencies [χ^2 (df = 2) = 17.00, p < 0.001] meaning that the disturbances are dependent on study site.

Looking at Figure 24, it shows that most of the pixels that had more than one disturbance are within the Impact Area. This can imply that there are disturbances to the vegetation within the Impact Area that aren't happening within the entirety of Smoky Hill ANGR or the Comparison Site.

Breaks	No. Pixels	Area (ha)	Percent with no Breaks	No. Pixels	Area (ha)	Percent with at Least 1 Break
Comparison Site	1373	7,326	93.78%	91	486	6.22%
Smoky Hill ANGR	1557	8,308	85.93%	255	1,361	14.07%
Impact Area	667	3,559	73.30%	243	1,297	26.70%

Table 19 Summary of the percent of pixels without a break and the amount of pixels with at least one break at the study areas.

Discussion and Conclusion

The overall trend for a majority of the pixels at all three study areas were greening up over the 11 years (Table 16). The Impact Area had more disturbances in trend than the other two sites and most of these disturbances responded with browning. Compared to the other two sites where more of the disturbances responded with greening up of vegetation (Table 18). The differences in response to a disturbance could be misleading because of when the NDVI value was taken and how vegetation responds to burning. Depending on when the NDVI image was taken the same burn could show a browning or greening response. This is a limitation of 16-day composite imagery with BFAST.

Even though the overall trend for all areas is the same there is a difference in the disturbances from the Impact Area compared to Smoky Hill ANGR (excluding the Impact Area) and the Comparison Site. The weather over the study period didn't show any significant trends for mean monthly temperature (Figure 5), maximum monthly temperature (Figure 6), minimum monthly temperature (Figure 7), and total monthly temperature (Figure 8) so weather trends are't significantly influencing the trend analysis. There is something happening in the Impact Area that is disturbing the vegetation, more than the other two sites, but isn't negatively influencing the overall vegetation trend of the site.

Knowing that military training affects the environment (Wilson 1988; Shaw *et al*., 1989; Whitecotton *et al*., 2000; Quist *et al*., 2003) and based on the results from this studies BFAST analysis it can be concluded that there are training activities happening within the Impact Area that are effecting the vegetation conditions. A similar study was done using BFAST on another military installation in Kansas, Fort Riley (Hutchinson *et al*., 2015). Both Smoky Hill ANGR and Fort Riley are comprised of mostly prairie land, are within proximity of each other, and have active ongoing training areas. The big difference between the two sites is the type of training happing at each. Smoky Hill ANGR is mainly used as a bombing range and Fort Riley is used for "on- and off-road field maneuvers (including tracked and wheeled combat vehicle operations), mortar and artillery fire, small arms fire, and aircraft flights (Hutchinson *et al*., 2015, p. 357)." Even with differences in training activities at the installations there are similarities between the two sites.

The training areas, at both locations, received more frequent disturbances in vegetation compared to the rest of the installations and their respective comparison sites. Which, is to be expected based on past research of military training environmental effects (Lathrop 1982;

Diersing *et al*., 1988; Wilson 1988; Shaw *et al*., 1989; Milchunas *et al*., 1999; Whitecotton *et al*., 2000; Quist *et al*., 2003; Leis *at el*., 2005; Althoff *et al*., 2009). Another similarity is that the military installations had different vegetation disturbances and responses compared to the non-military areas. The military installations are different from the non-military lands. With the similarities between the two sites there are also some notable differences.

To start off with the overall trend between the two areas is quite different. At Fort Riley 54% of the pixels were browning compared to only 12% at Smoky Hill ANGR. Fort Riley also had only 32% of is pixels without a break compared to 82% of Smoky Hill ANGR. Based on the differences in the two studies and knowing the difference in training activities it can be inferred that the training at Fort Riley is having greater negative vegetation impacts than the training at Smoky Hill ANGR. It also suggests that if the type of training at Fort Riley was implemented at Smoky Hill ANGR it would have adverse effects on the vegetation conditions.

To further this research more needs to be done to determine what is causing the increase in disturbances and the negative response to disturbances within the Impact Area. Is it direct effects of training or management practices like burning? It would also be interesting to do an analysis between the Impact Area of Fort Riley compared to the Impact Area at Smoky Hill ANGR to see how areas with similar training at different locations are acting.

Chapter 6 - Synthesis of Findings

Military training grounds are important, but the training on those lands can have impacts on the environment. Proper environmental assessments and management are necessary for the continued viability of the training grounds. For this study two separate analyses were done a contemporary burn history and a long term trend analysis at three study areas from 2001-2011. Based on these two studies the following conclusions can be made.

The Impact Area had more burning (Figure 15) and disturbances detected (Figure 24), from BFAST, than the rest of Smoky Hill ANGR and the Comparison Site. The vegetation response to the largest break within the Impact Area is also telling; 76% of the largest breaks responded with a negative vegetation response. This is what you would expect after a burning event. The NDVI values would be trending in a certain trajectory and then burning occurs, causing a dramatic decline in the NDVI values. Registering as a break from the trend in the BFAST analysis. The vegetation response after large disturbances found will BFAST indicate that burning could be causing the breaks. But, because of the way BFAST works burns could show up as a positive or negative response meaning that the responses indicator from BFAST might be misleading.

To determine if there was a relationship between burns and breaks separate Chi-squared contingency table analyses were run on the entirety of Smoky Hill ANGR and then the Comparison Site. The Smoky Hill ANGR results showed that there is significant relationship between burns and breaks [χ^2 (df = 66) = 262.52, $p << 0.001$] meaning that BFAST is detecting known disturbances. At the Comparison Site the results showed no relationship between burns and breaks [χ^2 (df = 55) = 44.01, $p > 0.5$]. An explanation for there being no relationship between burns and breaks at the Comparison Site could be there was not very many burned pixels or breaks detected. Only 6% of the pixels recorded one or more breaks and only 14% of the pixels had 2 or more burns. Most of the data points were zero. But, where there were a lot of burns, Smoky Hill ANGR, BFAST was able to pick up on the disturbances.

Another aspect analyzed was the relationship between breaks and overall trend found with BFAST. To determine if there was a relationship between the two a logistic regression was run on the entirety of Smoky Hill ANGR and then the Comparison Site. For Smoky Hill ANGR the coefficient estimate is 0.55 and $p << 0.0001$. There is a relationship between overall trend and disturbances. Then a McFadden test was run to determine if disturbances were a good predictor of trend. The McFadden result (3.23e-02) showed that disturbances are not a very good predictor of trend. For the Comparison Site the coefficient estimate is 0.98 and $p < 0.001$ and the McFadden value 0.02 is the same result as Smoky Hill ANGR. There is a relationship between overall trend and disturbances but disturbances are not a strong predictor of trend.

When comparing the results of this studies BFAST analysis to another BFAST study of a military installation in Kansas, Fort Riley, some similarities and differences exist. Two main similarities stick out between the two studies. One is that the impact areas at both sites are the most disturbed, recording more breaks in trend than outside of the training areas. Second is that the military installations are significantly different than the non-military reference sites. A main difference between the two sites is the overall trend. For the entirety of Smoky Hill ANGR only 12% of the pixels are browning compared to 54% at Fort Riley. This difference in overall trend could be a result of the different training regimes between Fort Riley and Smoky Hill ANGR. The training at Fort Riley seems to be having more negative effects on the overall vegetation condition and if the training at Fort Riley was moved to Smoky Hill ANGR it would have adverse effects on the vegetation conditions there.

Based on the results from both of these studies, burn history and time series analysis, I have concluded that BFAST is an effective and viable environmental management tool. It has limitations, like; how the first and last images in the time series have large influences on the overall trend and how using moderate resolution 16 day composite imagery smooths out disturbances within the overall trend. Even with these limitations BFAST was still able to detect known disturbances and add to the narrative that military installations are different from non-military lands. Using BFAST on MODIS 16 day composite imagery would be a helpful tool for land managers to be able to determine areas that might be over stressed and need a break or areas that have responded well to changes in management practices.

An area that still needs more research is further validation of the overall trend component. The validation method in this study had contradicting results to the BFAST analysis. The contradiction might have been because of the dates of usable imagery for the validation or that BFAST is not accurately capturing trend. More research needs to be done to validate the BFAST trend component. Another analysis that could be telling is comparing the Impact Area at Fort Riley to the Impact Area at Smoky Hill ANGR to see how areas with similar training at different locations are acting.

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Appendix A - BFAST Code and Documentation

loadZbfast {bfast} R Documentation

Break detection in the seasonal and trend component of a univariate time series

Description

Iterative break detection in seasonal and trend component of a time series. Seasonal breaks is a function that combines the iterative decomposition of time series into trend, seasonal and remainder components with significant break detection in the decomposed components of the time series.

Usage

bfast(Yt, h = 0.15, season = c("dummy","harmonic","none"), max.iter = NULL, breaks = NULL, hpc ="none")

Arguments

Yt	univariate time series to be analyzed. This should be an object of class "ts" with a frequency greater than one without NA's.
h	minimal segment size between potentially detected breaks in the trend model given as fraction relative to the sample size (i.e. the minimal number of observations in each segment divided by the total length of the timeseries.
season	the seasonal model used to fit the seasonal component and detect seasonal breaks (i.e. significant phenological change). There are three options: "dummy", "harmonic", or "none" where "dummy" is the model proposed in the first Remote Sensing of Environment paper and "harmonic" is the model used in the second Remote Sensing of Environment paper (See paper for more details) and where "none" indicates that no seasonal model will be fitted (i.e. St = 0). If there is no seasonal cycle (e.g. frequency of the time series is 1) "none" can be selected to avoid fitting a seasonal model.
max.iter	maximum amount of iterations allowed for estimation of breakpoints in seasonal and trend component.
breaks	integer specifying the maximal number of breaks to be calculated. By default the maximal number allowed by h is used.
hpc	A character specifying the high performance computing support. Default is "none", can be set to "foreach". Install the "foreach" package for hpc support.

<u>Details</u> : **To be completed.**

<u>Value</u>

An object of the class "bfast" is a list with the following elements:

Yt	equals the Yt used as input.
output	is a list with the following elements (for each iteration): Tt the fitted trend component St the fitted seasonal component Nt the noise or remainder component Vt equals the deseasonalized data Yt - St for each iteration bp.Vt output of the breakpoints function for the trend model ci.Vt output of the breakpoints confint function for the trend model Wt equals the detrended data Yt - Tt for each iteration bp.Vt output of the breakpoints function for the seasonal model ci.Vt output of the breakpoints confint function for the seasonal model
nobp	is a list with the following elements: nobp.Vt logical, TRUE if there are breakpoints detected

	nobp.Wt logical, TRUE if there are breakpoints detected
magnitude	magnitude of the biggest change detected in the trend component
Time	timing of the biggest change detected in the trend component

Author(s) : **Jan Verbesselt**

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See Also

plot.bfast for plotting of bfast() results.

breakpoints for more examples and background information about estimation of breakpoints in time series.

<u>Examples</u>

```
# Simulated Data
plot(simts) # stl object containing simulated NDVI time series

datats <- ts(rowSums(simts$time.series)) # sum of all the components (season,abrupt,remainder)
tsp(datats) <- tsp(simts$time.series) # assign correct time series attributes
plot(datats)

fit <- bfast(datats,h=0.15, season="dummy", max.iter=1)
plot(fit,sim=simts)
fit # prints out whether breakpoints are detected in the seasonal and trend component

# Real data
# The data should be a regular ts() object without NA's
# See Fig. 8 b in reference
plot(harvest, ylab="NDVI") # MODIS 16-day cleaned and interpolated NDVI time series

(rdist <- 10/length(harvest)) # ratio of distance between breaks (time steps) and length of the time series
fit <- bfast(harvest,h=rdist, season="harmonic", max.iter=1,breaks=2)
plot(fit)
plot(fit,type="trend",largest=TRUE)
plot(fit,type="all")

# output
niter <- length(fit$output) # nr of iterations
out <- fit$output[[niter]]  # output of results of the final fitted seasonal and trend models and nr of breakpoints in both.

# References
citation("bfast")

# For more info
?bfast
```

```
function (Yt, h = 0.15, season = c("dummy", "harmonic", "none"),
    max.iter = NULL, breaks = NULL, hpc = "none")
{
    season <- match.arg(season)
    ti <- time(Yt)
    f <- frequency(Yt)
    if (class(harvest) != "ts")
        stop("Not a time series object")
    output <- list()
    St <- stl(Yt, "periodic")$time.series[, "seasonal"]
    Tt <- 0
    if (season == "harmonic") {
        w <- 1/23
        tl <- 1:length(Yt)
        co <- cos(2 * pi * tl * w)
        si <- sin(2 * pi * tl * w)
        co2 <- cos(2 * pi * tl * w * 2)
        si2 <- sin(2 * pi * tl * w * 2)
        co3 <- cos(2 * pi * tl * w * 3)
        si3 <- sin(2 * pi * tl * w * 3)
        smod <- Wt ~ co + si + co2 + si2 + co3 + si3
    }
    else if (season == "dummy") {
        D <- seasonaldummy(Yt)
        D[rowSums(D) == 0, ] <- -1
        smod <- Wt ~ -1 + D
    }
    else if (season == "none") {
    }
    else stop("Not a correct seasonal model is selected ('harmonic' or 'dummy') ")
    Vt.bp <- 0
    Wt.bp <- 0
    CheckTimeTt <- 1
    CheckTimeSt <- 1
    i <- 0
    while ((!identical(CheckTimeTt, Vt.bp) | !identical(CheckTimeSt,
        Wt.bp)) & i < max.iter) {
        CheckTimeTt <- Vt.bp
        CheckTimeSt <- Wt.bp
        Vt <- Yt - St
        p.Vt <- sctest(efp(Vt ~ ti, h = h, type = "OLS-MOSUM"))
        if (p.Vt$p.value <= 0.05) {
            bp.Vt <- breakpoints(Vt ~ ti, h = h, breaks = breaks,
                hpc = hpc)
            nobp.Vt <- is.na(breakpoints(bp.Vt)[1])
        }
        else {
            nobp.Vt <- TRUE
            bp.Vt <- NA
        }
        if (nobp.Vt) {
            fm0 <- rlm(Vt ~ ti)
            Vt.bp <- 0
            Tt <- ts(fitted(fm0))
            tsp(Tt) <- tsp(Yt)
            ci.Vt <- NA
        }
        else {
            fm1 <- rlm(Vt ~ breakfactor(bp.Vt)/ti)
            ci.Vt <- confint(bp.Vt, het.err = FALSE)
            Vt.bp <- ci.Vt$confint[, 2]
            Tt <- ts(fitted(fm1))
```

```
        tsp(Tt) <- tsp(Yt)
    }
    if (season == "none") {
        Wt <- 0
        St <- 0
        bp.Wt <- NA
        ci.Wt <- NA
        nobp.Wt <- TRUE
    }
    else {
        Wt <- Yt - Tt
        bp.Wt <- breakpoints(smod, h = h, breaks = breaks,
            hpc = hpc)
        nobp.Wt <- is.na(breakpoints(bp.Wt)[1])
        if (nobp.Wt) {
            sm0 <- rlm(smod)
            St <- ts(fitted(sm0))
            tsp(St) <- tsp(Yt)
            Wt.bp <- 0
            ci.Wt <- NA
        }
        else {
            if (season == "dummy")
              sm1 <- rlm(Wt ~ -1 + D %in% breakfactor(bp.Wt))
            if (season == "harmonic")
              sm1 <- rlm(Wt ~ (co + si + co2 + si2 + co3 +
                si3) %in% breakfactor(bp.Wt))
            St <- ts(fitted(sm1))
            tsp(St) <- tsp(Yt)
            ci.Wt <- confint(bp.Wt, het.err = FALSE)
            Wt.bp <- ci.Wt$confint[, 2]
        }
    }
    i <- i + 1
    output[[i]] <- list(Tt = Tt, St = St, Nt = Yt - Tt -
        St, Vt = Vt, bp.Vt = bp.Vt, Vt.bp = Vt.bp, ci.Vt = ci.Vt,
        Wt = Wt, bp.Wt = bp.Wt, Wt.bp = Wt.bp, ci.Wt = ci.Wt)
}
if (!nobp.Vt) {
    Vt.nrbp <- length(bp.Vt$breakpoints)
    co <- coef(fm1)
    Mag <- matrix(NA, Vt.nrbp, 3)
    for (r in 1:Vt.nrbp) {
        if (r == 1)
            y1 <- co[1] + co[r + Vt.nrbp + 1] * ti[Vt.bp[r]]
        else y1 <- co[1] + co[r] + co[r + Vt.nrbp + 1] *
            ti[Vt.bp[r]]
        y2 <- (co[1] + co[r + 1]) + co[r + Vt.nrbp + 2] *
            ti[Vt.bp[r] + 1]
        Mag[r, 1] <- y1
        Mag[r, 2] <- y2
        Mag[r, 3] <- y2 - y1
    }
    index <- which.max(abs(Mag[, 3]))
    m.x <- rep(Vt.bp[index], 2)
    m.y <- c(Mag[index, 1], Mag[index, 2])
    Magnitude <- Mag[index, 3]
    Time <- Vt.bp[index]
}
else {
    m.x <- NA
    m.y <- NA
```

```
        Magnitude <- 0
        Time <- NA
        Mag <- 0
    }
    return(structure(list(Yt = Yt, output = output, nobp = list(Vt = nobp.Vt,
        Wt = nobp.Wt), Magnitude = Magnitude, Mags = Mag, Time = Time,
        jump = list(x = ti[m.x], y = m.y)), class = "bfast"))
}
<environment: namespace:bfast>
```

Load these packages in R:

zoo
sandwich
MASS
quadprog
tseries
strucchange
fracdiff
forecast
iterators
codetools
foreach
bfast

```
setwd("z:/Projects/RTLA/MODIS_Smoky/BFAST_Results ")
datafile <-"smoky_ndiv_table.csv"

inidata<-read.table(datafile,header=TRUE,sep = ",",dec = ".")
mdata<-as.matrix(inidata)
tpdata<-mdata
vmax<-dim(mdata)
#number of lines
vmax[1]
#number of columns
vmax[2]

for(count in 1:vmax[1])
{
poly_id<-tpdata[count,1]
ndvi<-tpdata[count,2:vmax[2]]
plot(ndvi)
tsdata<-ts(ndvi,frequency=23,start=c(2001,1))
dim(tsdata)<-NULL
#(rdist<-23/length(tsdata))
fits<-bfast(tsdata,h=0.10,season="harmonic",max.iter=1)
plot(fits)
fits2<-fits$Time
ts_trend_break_time<-t(fits2[1])
fits3<-fits$Magnitude
ts_trend_break_magnitude<-t(fits3[1])
fits4<-fits$output
fits4a<-fits4[[1]]$Vt.bp
fits4adata<-as.matrix(fits4a)
fits4amax<-dim(fits4adata)
ts_trend_nbbreak<-t(fits4amax[1])
results1<-ts_trend_break_time
aLine<-t(c(poly_id,results1))
write.table(aLine,file="trend_breaks_time_smoky.txt",append=TRUE,quote=FALSE,sep=",",eol="\n",na="NA",dec=".",row.na
mes=FALSE,col.names=FALSE,qmethod=c("escape","double"))
results2<-ts_trend_break_magnitude
aLine<-t(c(poly_id,results2))
write.table(aLine,file="trend_breaks_magnitude_smoky.txt",append=TRUE,quote=FALSE,sep=",",eol="\n",na="NA",dec=".",ro
w.names=FALSE,col.names=FALSE,qmethod=c("escape","double"))
results3<-ts_trend_nbbreak
aLine<-t(c(poly_id,results3))
write.table(aLine,file="trend_nbbreaks_smoky.txt",append=TRUE,quote=FALSE,sep=",",eol="\n",na="NA",de=".",row.names=
FALSE,col.names=FALSE,qmethod=c("escape","double"))
fits4b<-fits4[[1]]$Tt
results4<-fits4b
aLine<-t(c(poly_id,results4))
write.table(aLine,file="trend_bfast_smoky.txt",append=TRUE,quote=FALSE,sep=",",eol="\n",na="NA",dec=".",row.names=FA
LSE,col.names=FALSE,qmethod=c("escape","double"))
```

```
fits4c<-fits4[[1]]$Wt.bp
fits4cdata<-as.matrix(fits4c)
fits4cmax<-dim(fits4cdata)
ts_season_nbbreak<-t(fits4cmax[1])
results5<-ts_season_nbbreak
aLine<-t(c(poly_id,results5))
write.table(aLine,file="season_nbbreaks_smoky.txt",append=TRUE,quote=FALSE,sep=",",eol="\n",na="NA",de=".",row.names
=FALSE,col.names=FALSE,qmethod=c("escape","double"))
ts_season_breaks_time<-t(fits4cdata)
results6<- ts_season_breaks_time
aLine<- t(c(poly_id,results6))
write.table(aLine,file="season_breaks_time_smoky.txt",append=TRUE,quote=FALSE,sep=",",eol="\n",na="NA",de=".",row.na
mes=FALSE,col.names=FALSE,qmethod=c("escape","double"))
fits4d<-fits4[[1]]$St
results7<-fits4d
aLine<-t(c(poly_id,results7))
write.table(aLine,file="season_bfast_smoky.txt",append=TRUE,quote=FALSE,sep=",",eol="\n",na="NA",dec=".",row.names=F
ALSE,col.names=FALSE,qmethod=c("escape","double"))
}
```