California State University, Northridge

Differentiating Anthropogenic Rangeland Degradation from Climate Variability on Cimarron National Grassland in Morton County, Kansas

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By

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Abstract

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Degradation of public grazing land by cattle on Cimarron National Grassland in Morton County, Kansas, USA between 1991 and 2000 was studied using Landsat remote sensing data. The normalized difference vegetation index was calculated from the satellite data and used as an indicator of relative density and health of vegetation. Distinguishing the change in vegetation health due to natural factors (weather) and grazing is difficult because plant growth in arid and semiarid environments is often highly dependent on rainfall. Therefore, the climate signal must be removed from vegetation data prior to assessing human-induced degradation. To assess the change in vegetation health due to natural factors (weather), a regression model was developed based on the relationship between greenness and precipitation, and deviations from this model were attributed to grazing. These deviations (residuals) were studied to determine whether a relationship existed between them and grazing data. Residuals from this model were compared to both the number of days that grazing took place and animal units summed over three different timeframes individually. Correlation tests revealed a

significant negative correlation between NDVI residuals and the cumulative number of grazing days in many parts of the study area. Animal units were not significantly correlated with residuals. Future research into the best method for accumulating grazing data over different intervals is still needed. Results show that the residual trend method can effectively remove the climate signal from remotely sensed vegetation data.

Chapter 1 Introduction

Land degradation currently poses a serious threat to the environment and global food supplies. Over 250 million people in over 100 countries across the world are adversely affected by land degradation (Adger et al. 2001). The United Nations Convention to Combat Desertification defines land degradation as a decrease in biological or economic output of land, which can be caused by many factors including climate variability and land-use (Lal et al. 2012). Nearly a quarter of the globe is affected by degradation and as much as one-fifth of that land is agricultural (Bai et al. 2008). Overexploitation of natural resources by humans, particularly on arid and semiarid grasslands, has proven to be a difficult phenomenon to measure (Wang et al. 2012). This is largely because changes in vegetation growth in arid and semiarid environments are most often caused by rainfall variability (Wessels et al. 2007). For decades, debates over rangeland degradation and its causes invariably came down to two polar viewpoints, natural climate induced change versus anthropogenic degradation (Archer 2004). Many arid and semiarid regions of the world experience significant variability in precipitation each year, which often makes it difficult to detect human-induced degradation. Distinguishing vegetation responses to variability in rainfall from overgrazing is a complicated task that requires complex methods. The residual trend method, which was first proposed by Evans and Geerken (2004) and Archer (2004), is intended to ‘correct’ for rainfall variability and remove the climate signal from remotely sensed vegetation data. This paper seeks to analyze Landsat data using the residual trend method for Cimarron National Grassland (CNG).

Cimarron National Grassland (CNG), in southwest Kansas, USA, is a prime location to study rangeland degradation. This area was severely affected by the Dust Bowl of the 1930s, which was caused by drought and inappropriate agricultural practices. Prior to its establishment as a National Grassland, CNG underwent extensive restoration efforts to reestablish the topsoils and vegetation that would make the land capable of supporting seasonal cattle grazing (Lewis 1989). Since its inception, CNG has served over 100 cattle ranchers as a well-managed summertime grazing area for approximately 5,000 head of cattle. The grassland covers an area of 108,000 acres (43,000 hectares). Grazing operations are usually permitted each year between May 1 and October 31. However, the introduction of cattle is often delayed past May 1 during drought years until summer rains arrive. Cattle are never introduced prior to May 1. Stocking rates for grazing permits issued each year are based on the amount of rainfall from the year before and forage availability. CNG is dependent on precipitation and is not irrigated. In recent years the amount of suitable forage crop produced on CNG has been lower than normal and grazing allotments issued to ranchers by the US Forest Service have been reduced (Brewer, CNG Range Management Specialist, personal communication 2014). While these allotment reductions are most likely attributable to rainfall variability, an evaluation of possible anthropogenic degradation will provide CNG land managers with additional data enabling them to make more informed decisions regarding cattle grazing.

The residual trend method uses the normalized difference vegetation index (NDVI), which is a remotely sensed measure of green surface vegetation (Jensen 2007). This index is based on the concept that healthy green vegetation strongly absorbs red and

reflects near infrared (NIR) electromagnetic radiation (ibid.) and is calculated using the following equation:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}$$

Equation 1. Normalized Difference Vegetation Index

NDVI values can range between negative one and one, with increasing values indicating a higher level of healthy green vegetation (NASA Earth Observatory 2014). Typically, NDVI values for areas with non-desert vegetation ranges between 0.1 and 1. Desert vegetation, bare soil, and rocks generally have NDVI values between 0 and 0.1. Water and clouds usually have negative NDVI values (Office of Satellite and Product Operations 2014).

The residual trend method is used to remove the climate signal from remotely sensed vegetation data in arid and semiarid environments. This is necessary because vegetation in these parts of the world is often highly dependent on rainfall, which prevents researchers from modeling the effects of other variables such as grazing. The method involves regressing NDVI with precipitation data to model vegetation. Differences between observed and modelled NDVI values (the residuals) serve as a measure of variability in NDVI not attributable to rainfall (Evans and Geerken 2004; Archer 2004). This method has been widely used by various studies around the world to differentiate between anthropogenic degradation and climate variability (Wessels et al. 2012; Brinkman et al. 2011; Paudel and Anderson 2010; Wessels et al. 2007; Herrmann 2006; Evans and Geerken, 2004; Geerken and Ilaiwi, 2004; and Archer, 2004).

Despite the fact that the residual trend method holds great potential to provide a measure of anthropogenic rangeland degradation, few studies have compared results from

residual trend analysis to what the method is intended to measure, anthropogenic degradation. Consequently, it is not fully understood how grazing strategies might affect vegetation growth. Previous studies have all used data with spatial resolution that was several hundred meters, which is less informative on the local scale. Since Evans and Geerken's (2004) study, the residual trend method has not been compared to or evaluated with Landsat satellite imagery.

The objectives of this study were to assess the impacts of cattle grazing on vegetation growth and to evaluate the effectiveness of the residual trend method in removing the climate signal from arid vegetation using Landsat TM satellite imagery. The extent to which cattle grazing can affect vegetation growth was also evaluated. Attempts were made to both adjust the residual trend method to perform better with Landsat data and to develop a simpler way of modeling NDVI. To do this, changes in NDVI between observations were used instead of the vegetation index itself. Overall trends in residuals were not expected to show exceptionally strong degradation during the study period. However, the correlation between results from the residual trend analysis and CNG stocking figures was expected to be stronger than that between stocking data and changes in NDVI itself. The residual trend method is intended to remove noise associated with rainfall variability and amplify the signal from human-induced degradation. One would expect therefore that the residuals should be negatively correlated with cattle grazing. In order to answer this question, a reliable regression model must be developed to calculate residuals.

Chapter 2 Background

2.1 Precipitation as a Predictor of NDVI

NDVI has been shown to be highly correlated with rainfall (Wang et al. 2001; Schmidt and Karnieli 2000; du Plessis 1999; Nicholson et al. 1998; Paruelo and Lauenroth 1998; Yang et al. 1997; Le Houérou et al. 1988). Paruelo and Lauenroth (1998) studied this phenomenon in several locations across the western US, including the grasslands of Kansas. They found that significant variability in this correlation existed depending on vegetation type. Wang et al. (2005) measured the correlation between remotely sensed NDVI and in situ ground measurements of precipitation and temperature for the state of Kansas, including CNG. Data used by Wang et al. (2005) covered a nine-year period between 1989 and 1997; AVHRR data with 1.1-kilometer spatial resolution were used. Precipitation and temperature data were collected from over 400 weather stations across Kansas. Results revealed that the average correlation coefficient between NDVI and rainfall was 0.90 with a four-week lag between actual rainfall events and responses in NDVI. The correlation between temperature and NDVI was found to be relatively small.

The strong linear correlation between rainfall and NDVI in arid and semiarid environments makes it a good predictor variable for vegetation using simple linear regression. Measuring variability in precipitation can be used to model fluctuations in vegetation. An important aspect of this relationship is that the residuals from a regression model between precipitation and NDVI can serve as a measure of changes in vegetation caused by other unknown variables. The residuals are a measure of the variability in the response variable not explained by the regression model (Montgomery et al. 2012).

Variability in NDVI not explained by rainfall variability can be detected in the residuals of a regression model between the two. The variables that are responsible for the residuals, such as human-induced rangeland degradation, are often difficult to measure directly.

2.2 The Residual Trend Method

The residual trend method involves calculating the slope and intercept from a linear regression model with remotely sensed NDVI data as the dependent variable (y) and precipitation data as the independent variable (x). The slope and intercept are used in conjunction with precipitation data to calculate modelled NDVI values. Modeled values are subtracted from observed NDVI values to determine NDVI residuals, which can be analyzed for trends. The modelled values can be thought of as variability in NDVI caused by precipitation. Each residual observation represents variability in NDVI not caused by variability in rainfall. A negative trend in the NDVI residuals overtime would likely indicate that degradation occurred during the study period (Evens and Geerken 2004). This would result from NDVI being lower on average as the study period progressed, but with comparable amounts of rainfall. In order for the residual trend method to perform properly, the linear regression model must be run on a pixel-by-pixel basis (ibid.). This is the only way to negate the effects of vegetative, edaphic, and geomorphometric variability across a large study area (ibid.), all of which can be considered constant over a decadal study period (Paudel and Anderson 2010).

Previous studies have used various measures of net primary production (NPP) to analyze rangeland degradation. These methods typically involve either identifying $NDVI_{max}$ (annual maximum NDVI for one image each year) (e.g. Evans and Geerken

2004) or calculating seasonal ∑NDVI (the sum of NDVI for each growing season) (e.g. Wessels et al. 2012). Conversely, other researchers have used individual images to compile NDVI time series with multiple datasets for each year. Archer (2004) used ten-day maximum NDVI composite images to calculate residuals. Herrmann (2006) also used monthly maximum NDVI to calculate residuals. For this study, multiple images were used for each season.

Even though residual trend analysis is considered as an effective method to remove the climate signal from remotely sensed vegetation data, vegetation response lag time can cause variability in the results. Following a rainfall event, the amount of time it takes for vegetation to respond to increased soil moisture can vary; this is referred to as "lag time." The time it takes rainfall to accumulate and the lag in vegetation response must be determined prior to calculating the slope and intercept in a linear regression model between precipitation and NDVI. The lag time for a study area essentially defines how far back in time an accumulation of soil moisture should be used to model NDVI.

One method for determining rainfall lag and accumulation times that are best correlated with NDVI, described by Evans and Geerken (2004), involves calculating several hundred precipitation datasets using every possible combination of lag and accumulation over a given period. For example, cumulative precipitation can be calculated over 10-days, 20-days, 30-days creating a new rainfall series for each increment. These datasets can then be paired with NDVI data using a series of different lag times. Correlation tests are then run between NDVI and each possible rainfall lag and accumulation combination for each pixel in a study area.

Herrmann (2006) found that NDVI residuals vary significantly between sensors. Using Advanced Very High Resolution Radiometer (AVHRR) data with an 8-kilometer spatial resolution and *Satellite Pour l'Observation de la Terre* (SPOT) data with a 1-kilometer spatial resolution, Herrmann calculated NDVI residuals for several sites in the Sahel using a 3-month cumulative rainfall series. Results from her study revealed that there was a strong correlation between rainfall and NDVI for both instruments, but the places and times where correlations occurred were inconsistent between the two instruments.

The residual trend method cannot detect dominant vegetation change from palatable to non-palatable vegetation (Archer 2004), which has been classified as a form of degradation by other scientists (Wessels et al. 2007). It is likely that livestock preference for a particular forage crop (the most palatable) will lead to it being degraded first. Eventually, vegetation that is more palatable will become overgrazed, leaving room for non-palatable vegetation to grow. Simply put, cattle will not consume less palatable vegetation and as a result, less palatable vegetation may thrive in overgrazed areas. Such a change could result in no significant trends in NDVI residuals. Indeed this sort of degradation could theoretically result in positive NDVI trends because it can actually encourage the growth of some plant species.

Evans and Geerken (2004) compared NDVI residuals that were calculated using 8-kilometer AVHRR data to 30-meter Landsat TM NDVI data. They concluded that only major anthropogenic changes to the landscape could be detected using Landsat because of its coarse temporal resolution (16-days). Arguing that the low NDVI values in dryland areas should be compared at similar phenological stages following comparable rainfall

patterns, Evans and Geerken (2004) reported that subtle changes in NDVI resulting from overgrazing could not be detected using Landsat because of its longer revisit time. Nevertheless, Landsat TM time series data have been used to map trends in vegetation by many researchers. Pickup, Bastin, and Chewings (1994) used Landsat data to monitor vegetation trends caused by grazing pressure in arid grasslands a decade before the residual trend method was first presented. In fact, several programs using Landsat data to monitor trends in vegetation have been in place for decades (Wallace, Behn, and Furby 2006). Landsat is the longest running satellite remote sensing program and the length of possible time series warrants further research into using these data to calculate and analyze residual trends.

Sonnenschein et al. (2011) differentiated between “land cover conversions” and “land cover modifications” and suggested coarser spatial resolution data (e.g. MODIS with its 250-meter resolution) are in fact less likely to detect subtle changes in land cover. They argued that larger pixel size (typically on a kilometer scale) fails to detect modifications on the often-fragmented human landscape. Wiegand et al. (2004) used study plots to measure vegetation biomass in situ in semiarid South African grasslands, which they then analyzed in relation to basal area. They found that biomass production relative to basal area did not vary significantly between degraded and non-degraded sites. Wiegand et al. (2004) concluded that the reduction or fragmentation of basal area leads to a decline in net biomass production in degraded areas. The level of fragmentation is likely to be more measurable using finer spatial resolution data from Landsat because denuded areas between patches would be more discernable.

In addition to different paradigms concerning the effectiveness of remote sensing data at different spatial and temporal resolutions, there were once other problems associated with using Landsat satellite imagery. One of the greatest obstacles that had to be negotiated was purchasing imagery (Sonnenschein et al. 2011). Additionally, preprocessing the data to correct for inherent noise (radiometric, geometric, and atmospheric corrections) was also a major issue (Coppin et al. 2004) that complicated NDVI time series analysis exponentially. Today, Landsat data are available free of charge and preprocessed through the US Geological Survey (Landsat Data Access 2015). With fewer hurdles to overcome, research can be conducted on a much finer spatial scale appropriate to more subtle environmental modifications by humans.

With the exception of Archer (2004) and Paudel and Anderson (2010), all previous studies using the residual trend method were carried out in areas where grazing statistics were unavailable. This paper seeks to measure the correlation between residuals and cattle grazing figures. All previous studies used NDVI data with daily temporal resolution and several hundred meter spatial resolution to calculate residuals (e.g. Wessels, Bergh, and Scholes 2012; Brinkman et al. 2011; Paudel and Anderson 2010; Wessels et al. 2007; Herrmann 2006; Evans and Geerken 2004; Geerken and Ilaiwi 2004; and Archer 2004). In order to obtain results that are comparable in scale to grazing data available on CNG, higher spatial resolution data such as Landsat NDVI must be used.

Chapter 3 Study Area

The study area is located almost entirely in Morton County, southwest Kansas, bordering the Oklahoma panhandle to the south and Colorado to the west. The elevation is approximately 1125 meters in the west and 960 meters in the east (Kansas Geological Survey 2004). Mean annual precipitation is less than 450 millimeters per year (US National Center for Environmental Information 2015) and the mean annual temperature is 13 degrees Celsius (Kansas Geological Survey 2004). Approximately 80% of the annual precipitation falls between March and September (US National Center for Environmental Information 2015). The climate is considered semiarid with frequent winds of up to 25 kilometers per hour and high evapotranspiration (Guest 1968). Morton County is a mostly flat, featureless plain intersected by the Cimarron River (Kansas Geological Survey 2004). Allotments north of the river contain some varied sloping terrain, while those to the south fall within the floodplain of the river. Approximately 30% of Morton County is covered by sand dunes, forming small and broad hills locally (ibid.).

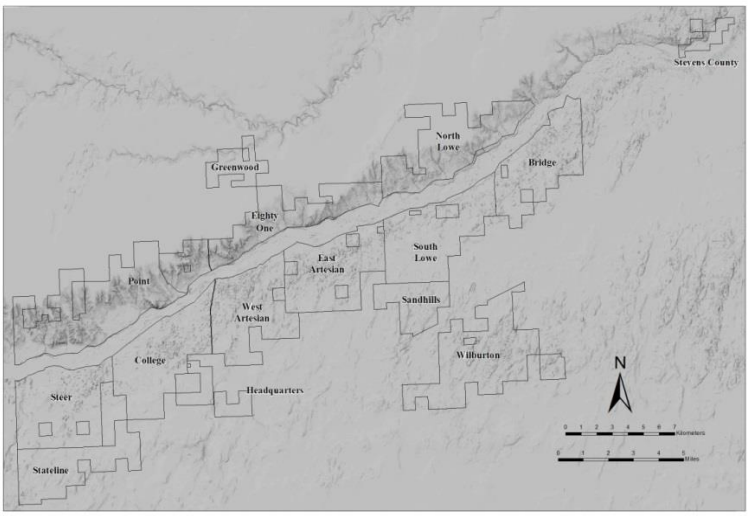


Plate 1. Grazing allotments of Cimarron National Grass Land analyzed in this study. The shaded relief was included to illustrate terrain.

3.1 Agricultural History

Southwest Kansas was adversely affected by the American Dust Bowl of the 1930s (Hurt 1985). Poor rangeland management and drought created a situation that led to severe wind erosion across the Great Plains (Kassas 1995). Marginal croplands, areas with soils that are difficult to exploit on a yearly basis, were the hardest hit by the Dust Bowl and virtually all of the topsoils were stripped completely by relentless dust storms (Hornbeck 2009). Decades of crop planting and overgrazing led to near total degradation in the area, which took twenty years of intensive stabilization and reseeding by the US Soil Conservation Service to restore (Guest 1968).

In the years preceding the Dust Bowl, environmental scientists were already advocating government intervention to prevent further overexploitation in these areas and to restore the land (Hurt 1985). As part of the New Deal, several government programs aimed at acquiring marginal lands were developed (Guest 1968). In the states with marginal croplands hit hardest by the Dust Bowl, there were four government land purchasing programs designed to acquire property from distressed farmers and restore them into well-managed grasslands (Hurt 1985). One of these was the Morton County Project, in southwest Kansas (ibid.). Land purchased as part of this study was permanently transferred to the US Forest Service and named Cimarron National Grassland in 1960 (Guest 1968). The Cimarron Valley is subject to frequent high winds and torrential summer monsoons that, when combined with vegetation stress, can lead to rapid and severe land degradation. Consequently, sustainable land-use practices are critical to preventing degradation (Schumacher and Atkins 1965).

3.2 Grass Species Found on CNG

Following the Dust Bowl, seeds from many native grass species were in short supply for restoration efforts. Only three species of native seeds were available in large quantities and typically made up 75% of the seed mixtures (Schumacher and Atkins 1965). Kuhn et al. (2011) conducted the first floristic inventory on CNG in 2008. Their inventory report provides the only recent description of dominant grass species on CNG.

All of the historically seeded and contemporary grass species listed in Table 1 are perennials. It often takes at least a full year for perennials to establish. Any disturbance would lead to increased propagation of annuals. This observation may suggest that degradation is low on CNG. However, this would not necessarily indicate that changes in vegetation vigor caused by grazing could not be detected. Subtle changes in plant growth could still occur following years with heavier than normal grazing or with less than normal rainfall.

Common Name	Scientific Name	Grazing Suitability
purple threeawn*	*Aristida purpurea var. longiseta*	Abundance tends to increase with overgrazing, as grasses that are more palatable are preferred by cattle, may serve as an indicator of overgrazing (Tilley and St. John 2014)
blue grama*,**	*Bouteloua gracilis**	Grazing should be deferred once every two to three years, forms sod under heavy grazing pressure (Wynia 2007)
buffalograss*,**	*Bouteloua dactyloides**	Highly palatable, rotational grazing required (Brakie 2013)
western wheatgrass*	*Elymus smithii*	Preferred forage crop for cattle, this species can tolerate heavy grazing (Ogle, St. John, and Winslow. 2009)
ring muhly*	*Muhlenbergia torreyi*	Generally considered a sign of overgrazing (Milchunas 2006)
sand dropseed*	*Sporobolus cryptandrus*	Palatability varies depending on stage in development and location, tolerates moderate grazing once established (Smith 2013)
sideoats grama**	*Bouteloua curtipendula*	Highly palatable, longer growing season than many other species, not resistant to overgrazing (Chadwick 2003)
sand lovegrass**	*Eragrostis trichodes**	Will show decrease in stand following grazing pressure, should not be closely grazed at any time (Wynia 2008a)
sand bluestem**	*Andropogon hallii*	Performs well under proper grazing management and is preferred by livestock (Wynia 2008b)
little bluestem**	*Schizachyrium scoparium*	Increases following season long grazing, has a lower palatability than other species late in the grazing season (Tober and Jensen 2013)

Table 1. Native Grass species on Cimarron National Grassland. * Dominant grass species found on CNG according to 2008 floristic inventory (Kuhn et al. 2011). ** Grass species planted on CNG during restoration efforts ca. 1930-1950 (Schumacher and Atkins 1965)

Approximately 30% of CNG consists of sand dunes, the majority of which are located south of the Cimarron River. According to Kuhn et al. (2011) these areas, which they classified as sandsage prairie, are dominated by shrubs, *Artemisia filifolia* (sand sage), *Ericameria nauseosa* (rabbitbrush), *and Yucca glauca* (narrowleaf yucca). Areas surrounding the Cimarron River, which flows across CNG from the northeast to the southwest, were not analyzed in this studied. Fortunately, cattle grazing on this portion of CNG is separated from other allotments.

Detailed maps indicating where dominant grass species differed spatially on CNG were not available. Based on the information above, it appears that vegetation communities vary across CNG and areas may respond to grazing differently. Many of the dominant vegetation types on CNG are less palatable and tend to increase in response to heavier grazing. However, severe degradation comparable to the Dust Bowl was not expected to have occurred on CNG during the study period.

Chapter 4 Data and Methods

Data were analyzed using two complimentary methods. The primary method was based on examining relationships between NDVI, precipitation, and cattle stocking information spatially on a continuous thirty-meter grid using GRASS GIS. The second method, which was not used as extensively, consisted of calculating mean image values for all of the raster datasets and studying them as tabular data in Microsoft Excel. This yielded two different sets of results, image results calculated for each 30-meter pixel and mean tabular results. Tabular tests, although lacking any spatial information and aggregated to the allotment level, were used to graph many of the results. This was necessary in order to analyze the data as a whole because the entire study area consisted of over 350,000 thirty-meter pixels. Image results likely yielded a more accurate description of the effects of cattle grazing on CNG as they provided greater insight into local phenomena. Tabular results allowed for comprehensive descriptions that were interpreted in a more general sense.

4.1 Normalized Difference Vegetation Index

NDVI data derived from Landsat 5 surface reflectance images with a 30-meter spatial resolution spanning ten-years (1991-2000) were used. Initially, data from later years were considered for this study (2000-2010). However, after further examination it was determined that many of the Landsat 5 scenes for several growing seasons from 2001 onward were not usable due to several issues including cloud cover. The surface reflectance images were processed by the US Geologic Survey's (USGS) Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS). NDVI derived from these data were calculated by USGS on request and downloaded from the Earth Science

Processing Architecture (ESPA) website (2014). Prior to requesting the NDVI data from ESPA, a list of Landsat scenes with metadata available for the study area was created on the USGS Earth Explorer website (earthexplorer.usgs.gov) to verify minimal cloud cover and image quality. LEDAPs software employs atmospheric correction methods similar to those used for Moderate Resolution Imaging Spectroradiometer (MODIS) to calculate surface reflectance. These atmospherically corrected data, referred to as Landsat Surface Reflectance Climate Data Record (CDR), are generated with LEDAPS software using water vapor, ozone, geopotential height, aerosol optical thickness, and elevation as inputs (Masek et al. 2006).

Eighty cloud free NDVI images collected between 1991 and 2000 were initially downloaded. Data were imported into a new GRASS GIS database location. The images with the highest mean NDVI values for each year were identified using the Univariate Raster Statistics tool. The image with the highest mean values for each year was considered the peak NDVI and all cloud free images preceding it through late February were used in further analysis. Forty cloud-free images collected during the growing season (those collected after late-February and before peak NDVI) were identified using this method.

ΔNDVI were calculated by subtracting each image in the NDVI time-series from the image preceding it for each year:

$$\Delta NDVI_2 = NDVI_2 - NDVI_1$$

Equation 2. Differenced NDVI (ΔNDVI)

In some instances, pixel values from the previous image were greater than the next image values, which resulted in negative ΔNDVI. Pixels with negative ΔNDVI values were not removed or modified in any way. The method for calculating ΔNDVI was not applied

across years. This reduced the number of images for further analysis to thirty. The NDVI images were sorted and titled based on the day of acquisition in Julian date format (e.g. an image collected on December 31, 1995 would have been labeled NDVI_1995365)

4.2 Precipitation

Daily precipitation data from the Northwest Alliance for Computational Science and Engineering's website (www.nacse.org 2015) were used. The rainfall data were downloaded in Band Interleaved by Line (BIL) format and imported into a new GRASS GIS database location separate from the NDVI location. This dataset is derived using the Parameter-elevation Relationship and Independent Slopes Model (PRISM) interpolation method (Daly et al. 2008). The PRISM model is used to interpolate precipitation data using digital elevation models (DEM) and rainfall measurements collected by the National Weather Service's Cooperative Observer Network (COOP). Each of the over 3600 daily precipitation datasets used had a 4-kilometer spatial resolution.

Using ΔNDVI as opposed to actual NDVI provided a much simpler way of calculating the precipitation inputs for the linear regression model. Lists of daily precipitation images corresponding to the time between NDVI image acquisition dates were generated in Microsoft Excel. These lists were added to a Grass GIS command script to sum rainfall between NDVI images used to calculate ΔNDVI. Three different precipitation lag times were used: zero, two-weeks, and four-weeks. These lag times were calculated by adding an additional two or four weeks prior to the time between image dates (typically 16 days apart). For example, if the image for ΔNDVI on Julian date 132 was calculated by subtracting NDVI data collected on Julian date 116, then the two-week

lag precipitation dataset for ΔNDVI Julian date 132 was calculated by summing the precipitation that fell between Julian dates 102 and 132 (116 – 14 = 102).

The cumulative rainfall images were then imported into the NDVI GRASS database location. These rainfall data were reprojected into North American Datum 1983 Universal Transverse Mercator System (UTM), clipped to the extent of the study area, and resampled from four-kilometers to 30-meter spatial resolution as part of the import process using the r.proj tool in GRASS GIS (Schroeder 2012).

Plate 2. Comparison of precipitation maps based on interpolation method, bilinear (left) and near (right). Both mapsets were derived from PRISM data with a 4-kilometer spatial resolution and resampled to 30-meters

Two interpolation methods were used as part of the resampling process, near and bilinear. This created six different precipitation series to be tested in the model, three accumulation times with two different resampling methods. The near interpolation method for resampling assigns each new raster cell value the closest cell value in the dataset from which it was derived. This method does not actually change any of the new raster's cell values; it simply "cuts" each pixel into smaller pixels with the same values. The bilinear interpolation method for resampling uses the mean weighted distance of four surrounding cells from the input dataset to create a smoother raster map that is less "block" like. The bilinear interpolation method is recommended for continuous data, such

as rainfall (ibid.). Nonetheless, both methods were used in order to determine if bilinear interpolation would in fact yield stronger results when resampling data from 4000 to 30-meters spatial resolution

Working in southern Africa, Wessels et al. (2007) and Wessels et al. (2012) used a logarithmic transformation to rescale precipitation data prior to modeling NDVI. Both studies concluded that the transformation, often referred to as a linear-log regression method, was more effective at modeling NDVI. This method was applied using the zero-lag precipitation dataset, but was not utilized further because the r^2 value in this case was lower than using simple linear regression.

4.3 Cattle Grazing Data

Fifteen of CNG's 30 grazing allotments were scattered or noncontiguous, meaning that some grazing permits were issued for multiple fields, but reported as a single unit. Determining how many cattle were in one section of an allotment versus another was not possible. As a result, only contiguous grazing allotments were used in the analysis. Lands surrounding the Cimarron River, which are managed as a separate grazing allotment, were also not included in the analysis because it is not likely that vegetation in that region rely entirely on rainfall. This reduced the size of the study area from approximately 108,000 acres (43,000 hectares) to 82,000 acres (33,000 hectares).

CNG grazing allotments are administered by the US Government. As a result, grazing numbers and duration are considered public record, which are available on request from the US Forest Service. Grazing permits are sold per head of cattle for an allotted amount of time each year. Number of head, the type of cattle grazing (cattle class), and the acreage for each allotment was used to calculate animal units days per acre

(AUD/a). Three cattle classes are allowed to graze on CNG: cow/calf pairs, cows only, and steers. According to Waller, Moser, and Anderson (1986), one cow with a three-month old calf is equal to 1.3 animal units (AU), one single cow is equal to one AU, and one yearling steer is equal to 0.7 AU. The number of cow/calf pairs, single cows, or steers in each allotment was multiplied by AU factors listed above. Animal units were then divided by the number of acres in its respective unit, hereafter referred to as AUD/a. The equation below was used to calculate AUD/a for each cattle class per allotment:

$$\mathrm{AUD/a} = \left(\frac{(\text{Number of Cattle in one class} * \text{AU Factor})}{\text{Area}}\right)$$

Equation 3. Animal Unit Days per Acre (AUD/a)

In cases where allotments contained multiple cattle classes, AUD/a data were calculated separately for each class and then summed. A table was generated with AUD/a values for every day during the study period corresponding to each allotment. The table was then joined to a list of all thirty ΔNDVI images with their respective dates and AUD/a values were summed over three different periods starting at each image acquisition date and extending back over time. The three periods used to calculate cumulative cattle grazing series were based on the time between image acquisition dates (the same periods used for precipitation inputs), six-months prior, and one-year prior. Essentially, daily animal units per acre were summed over different periods prior to when ΔNDVI data were collected. These data are hereafter referred to as ‘X time’ cumulative AUD/a (e.g. 6-months cumulative AUD/a).

One limitation to using animal units is that the exact weight of livestock is rarely recorded and the animal unit factors used were for average sized cattle. Animal units should be factored differently for cattle based on size (Waller, Moser, and Anderson

1986). The AU factors for average sized cattle were used because it was impossible to determine the size of cattle based on grazing permit data. It is conceivable that all of the cattle in Morton County during the 1990s were larger or smaller than the national average. Moreover, the cow/calf pair factor used assumed that the calves were all still nursing. However, it is impossible to determine if some of the calves had already been weaned and which allotments they grazed. Calculating precise animal units for multiple herds of cattle over the course of several years is simply not feasible and this may have affected the results.

In order to address the issues with calculating animal units, additional correlation tests were run using the number of days that grazing occurred prior to NDVI acquisition dates. These data were calculated by summing the number of days cattle grazing took place for each allotment. The actual number of cattle stocked and the acreage for each allotment were not included in the grazing day data. The grazing day and AUD/a data were imported into GRASS GIS and joined to a polygon shapefile of the study area by grazing allotment. Both grazing series were then converted from polygonal vector data into 30-meter raster grids.

Archer (2004) found that less “conservative” grazing strategies, where cattle were stocked for longer periods or with shorter fallow periods were related to lower overall NDVI and therefore lower residuals. However, Archer (2004) found no correlation between residuals and stocking density. Methods outlined above were intended to be similar to Archer (2004). Comparison between residuals and animal units alone was not attempted. As a product of grazing time and animal units, the AUD/a series served as a measure of animal units because any analysis using this dataset could be compared to

results derived from the prior grazing day series. In effect, analyzing animal units alone was unnecessary because this variable was reflected in the AUD/a series. .

4.4 Regression Modeling and Correlation Testing

ΔNDVI images were modeled using the Regression Series tool (r.regression.series) in GRASS GIS version 7.1. The r.regression.series tool was created to calculate linear regression parameters between two time series, e.g. NDVI and precipitation (Metz 2014). The Regression Series tool calculates a simple linear regression model for each pixel from two raster series. With this method, each of the 350,000 ground cells within the study area is treated as a distinct set of observations with one data point from each cell in the time series. The output of the Regression Series tool is a new image with cell values corresponding to linear regression parameters (e.g. coefficient of determination, slope, or offset) calculated for each pixel.

Seven r^2 images were generated independently using the different precipitation datasets as the explanatory variable and ΔNDVI as the response variable. The r^2 dataset with the highest mean value was then identified and the slope (parameter a) and offset (parameter b) from that model were calculated. These two images and the precipitation series from which they were derived were used to calculate modelled ΔNDVI using the slope-intercept equation below:

$$\Delta\mathrm{NDVI}_{\mathrm{model}} = (\mathrm{slope} \times \mathrm{cumulative\ rainfall}) + \mathrm{offset}$$

Equation 4. Modelled ΔNDVI

Residual images were then calculated for each of the original images by subtracting modelled ΔNDVI from observed:

$$\Delta\mathrm{NDVI}_{\mathrm{residual}} = \Delta\mathrm{NDVI}_{\mathrm{observed}} - \Delta\mathrm{NDVI}_{\mathrm{model}}$$

Equation 5. ΔNDVI residuals

One ΔNDVI residual image was calculated for each of the 30 images within the time series. The mean ΔNDVI pixel values were then calculated in GRASS GIS and exported into Microsoft Excel.

One assumption of linear regression modelling is that variance in the residuals does not covary with fitted values (Hyndman and Athanasopoulos 2014). Archer (2004) used a correlation test between modeled NDVI and residuals to test her model for this assumption. Paudel and Anderson (2010) tested their model by comparing residuals to rainfall. Both methods were used to test this assumption. If the residuals from a linear regression model tend to covary with either the dependent or the independent variable, then the relationship between x and y is likely not linear. In addition to these two complimentary methods, an F-test was run for each pixel in the study area using the Regression Series tool in GRASS GIS. The F-test, also known as analysis of variance (ANOVA), is used to test whether there is a significant difference between r^2 and zero (McGrew and Monroe 2009). Results from the F-test were then compared to the critical value corresponding to 95% confidence ($F = 4.17$) with one independent variable and 30 observations (Butler 1985).

Upon verifying that the assumptions were met and the model was valid, correlation tests were run between ΔNDVI residuals and all six grazing datasets individually (the AUD/a series and the grazing day series for 0, 6, and 12-months prior). Correlation tests were completed on the pixel level. Thirty datasets were used in the analysis. Accordingly, the degrees of freedom (df) for every pixel correlation value was 28. This simplified significance testing of results as each pixel could be compared to a critical value based solely on a desired confidence level. In this way, each pixel within

the study area could be reclassified based on the correlation coefficient (r value) being equal to or greater than a critical value corresponding to one of four significance levels (90%, 95%, 97.5%, and 99.5% confidence). R-values were evaluated according to a one-tailed significance since the correlation between ΔNDVI residuals and grazing data was expected to be negative. Table 2 below lists the critical r-values and the corresponding significance values.

	Significance	
Critical r value between ΔNDVI residuals and grazing data	Two-tailed	One-tailed
-0.241	0.2	0.1
-0.306	0.1	0.05
-0.361	0.05	0.025
-0.463	0.01	0.005

Table 2. Critical values for Pearson's correlation coefficients when n=30 (Butler 1985)

Residuals were calculated to remove the climate signal. In order to test whether this goal was met, grazing data were also compared to ΔNDVI and NDVI time series individually (Appendix I). Results from these tests were compared to both the one and two-tailed critical values in Table 2. The one-tailed test was used to compare results to those from the residuals and the two-tailed test was used to analyze the relationship overall.

4.5 Environmental Analysis

Finally, results from the correlation test between ΔNDVI residuals and grazing data were compared to different land cover and soil types across the study area using the zonal statistics tool in GRASS GIS. The National Land Cover Database (NLCD) produced by USGS in 1992 did not differentiate between grassland and shrub land. Consequently, the 1992 NLCD, which corresponded to the earliest period for this study, was not used. The 2001 NLCD was used instead. Soil data obtained from the Natural

Resources Conservation Service's (NRCS) (2015) Soil Survey Geographic Database (SSURGO) were compared to results based on soil type. Determining which land cover or soil types were most susceptible to degradation was beyond the scope of this study. However, identifying different environmental categories that might covary with results could provide a better description of where grazing appeared to yield the greatest effect on CNG during the study period.

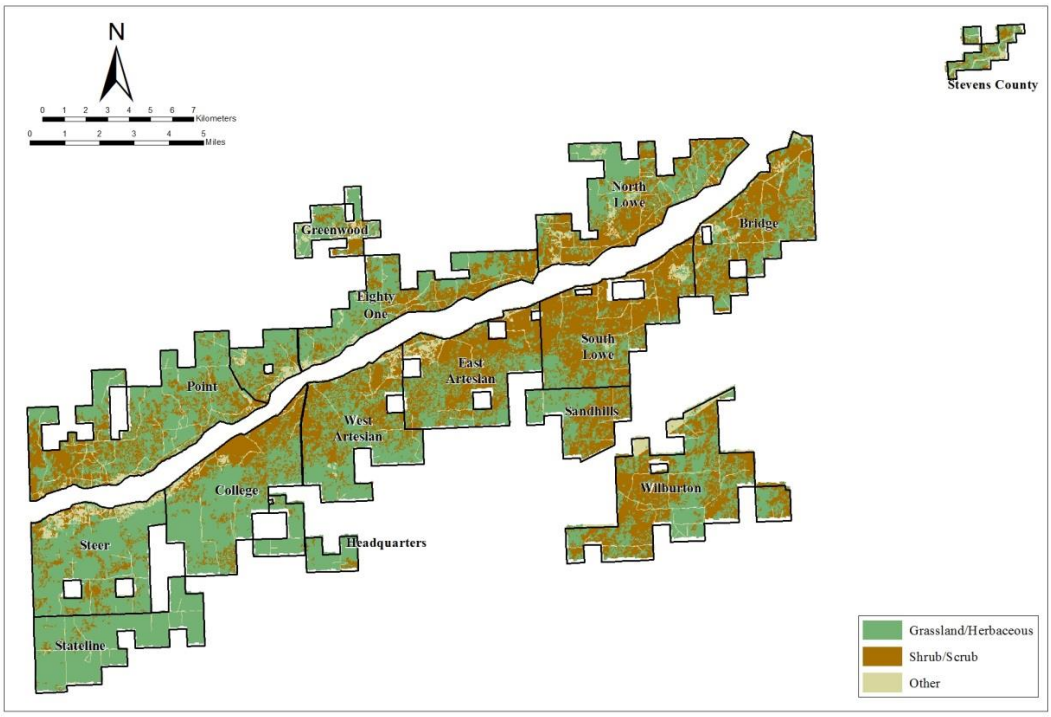


Plate 3. Land cover types found on Cimarron National Grassland according to 2001 National Land Cover Database (Multi-Resolution Land Characteristics Consortium 2015).

Soils within the study area were first classified into two very broad categories, loamy soils and sandy soils. Most of the areas north of the Cimarron River contain loamy soils; areas to the south primarily contain sandy soils. The NRCS uses Map Units (MU) to delineate and classify different areas having soils with "unique properties, interpretations, and productivity" (Natural Resources Conservation Service 2015). Map units that covered at least 1% of the study area (approximately 820 acres) were compared

to correlation test results between ΔNDVI residual and grazing data. There were 15 different soil types that covered several allotments that ranged in size from approximately 1,000 to 15,000 acres (400 to 6,000 hectares). This method of analysis was intended to identify if certain soil types were more vulnerable to grazing pressure than other types.

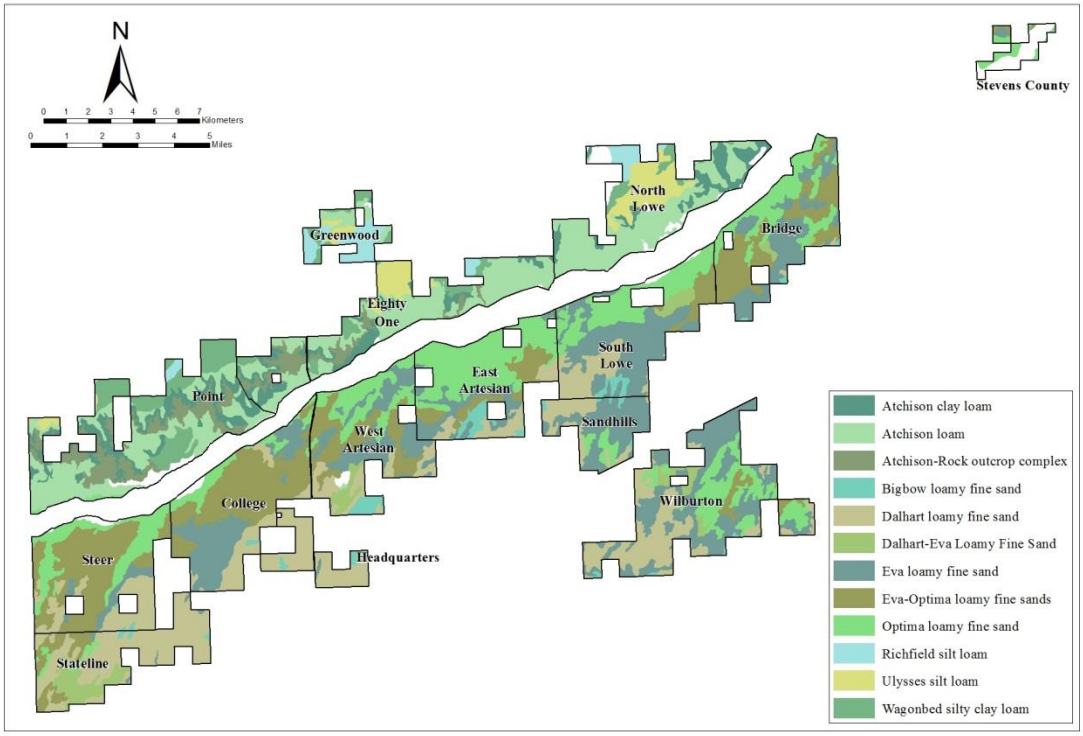


Plate 4. Soils found on Cimarron National Grassland according to SSURGO database (Natural Resources Conservation Service 2015)

Chapter 5 Results

5.1 Linear Regression Models

Analysis of NDVI time series data revealed that the growing season generally peaked between late June and early August (mean annual peak NDVI was 14 July +/- 20 days). The time between image acquisition dates, which was used to calculate one of the three rainfall series, varied because many cloud free image dates were preceded or followed by cloudy images (mean time between image dates = 37 days, maximum = 112, minimum = 16 days). Results were independent of whether bilinear or nearest interpolation methods were used in spite of the data appearing somewhat different when plotted on a map (Plate 2). Consequently, rainfall data that were resampled with the bilinear interpolation method were used in all further analysis. Results from the linear regression models also showed little to no difference within the first one thousandth in mean r^2 values between different resampling methods.

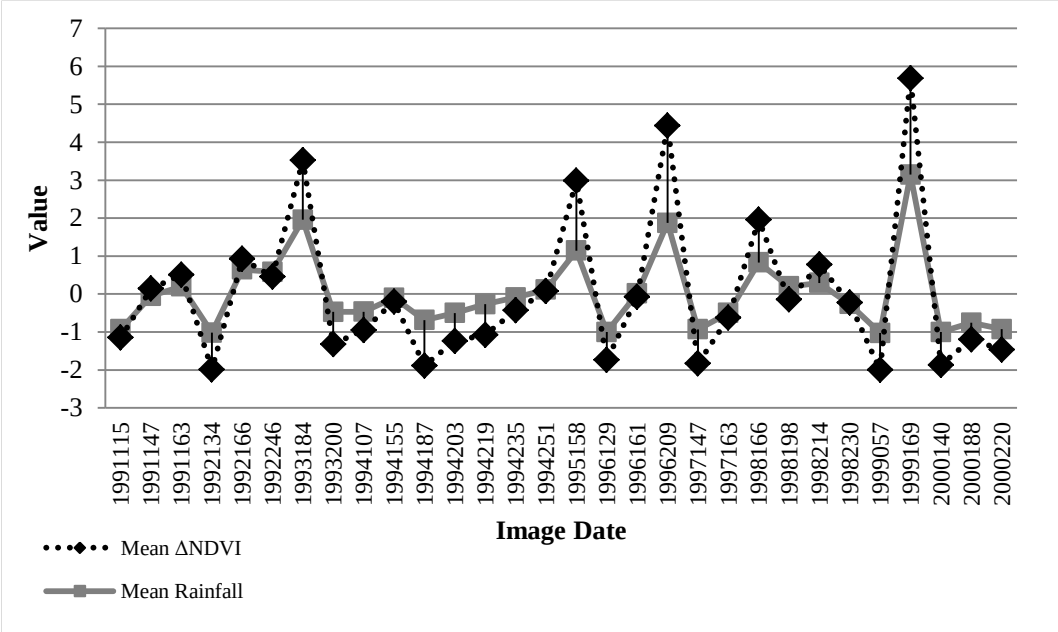


Figure 1. Comparison between mean ΔNDVI and cumulative rainfall. Z-scores were computed for each time series in order to scale the data in a similar fashion. The image dates (x-axis) are in Julian date format with a four-digit year and three-digit day of the year (e.g. 1997365 = December 31, 1997).

The similarities between the ΔNDVI and cumulative precipitation series seen in Figure 1 illustrate the strong correlation between the two datasets. Similar to other research findings cited above, there does appear to be a strong relationship between rainfall and biomass in arid and semi-arid environments. These results may also be the first to demonstrate that this relationship can be extended to changes in vegetation and rainfall between observations.

The ΔNDVI model results indicated that changes in vegetation between image dates were best correlated with the cumulative rainfall dataset having zero lag time (image mean r^2=0.604). The two and four-week lag precipitation datasets both yielded moderate r^2 results with ΔNDVI (image mean r^2 = 0.535 and 0.462, respectively). It must be stressed that each 30-meter square pixel within the study area was modeled independently and that over 350,000 r^2 values were calculated. Some regions within the study area had very high r^2 values (image maximum r^2= 0.898) while other areas had low r^2 values (image minimum r^2= 0). Tabular results between the mean ΔNDVI values for each image and its respective mean precipitation values indicated that there was a strong correlation between the two (tabular r^2= 0.849).

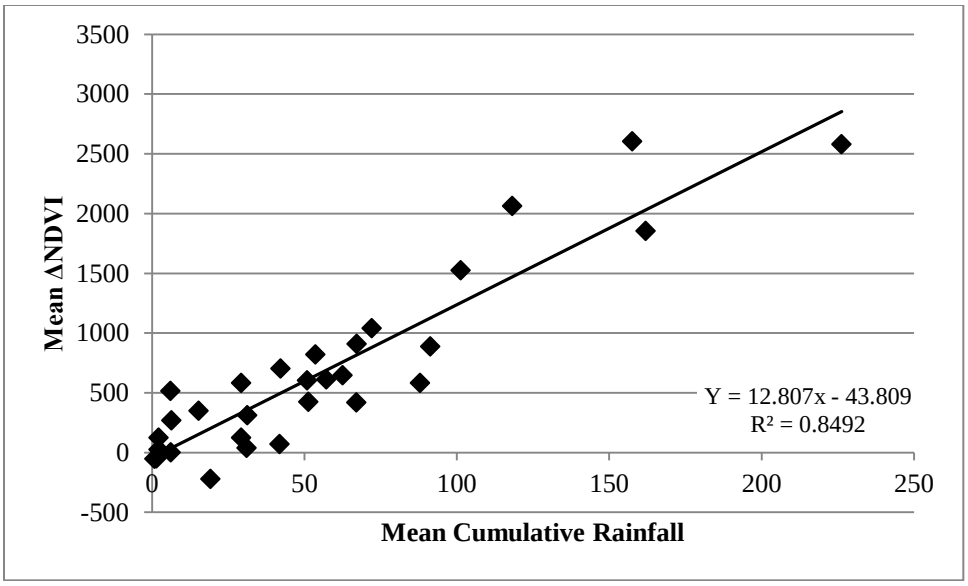


Figure 2. Scatter plot comparing mean cumulative rainfall (x) with zero-lag time and mean ΔNDVI (y).

The frequency histogram of r^2 results below (Figure 3) best illustrates the relationship between ΔNDVI and different rainfall lag times. This graph also provides an indication of how well the data were correlated. Descriptive statistics of r^2 results for each allotment (Table 3) do not appear to show any major differences in results depending on grazing area. The linear regression model with zero lag time was used for all further analysis because it yielded the highest r^2 values overall.

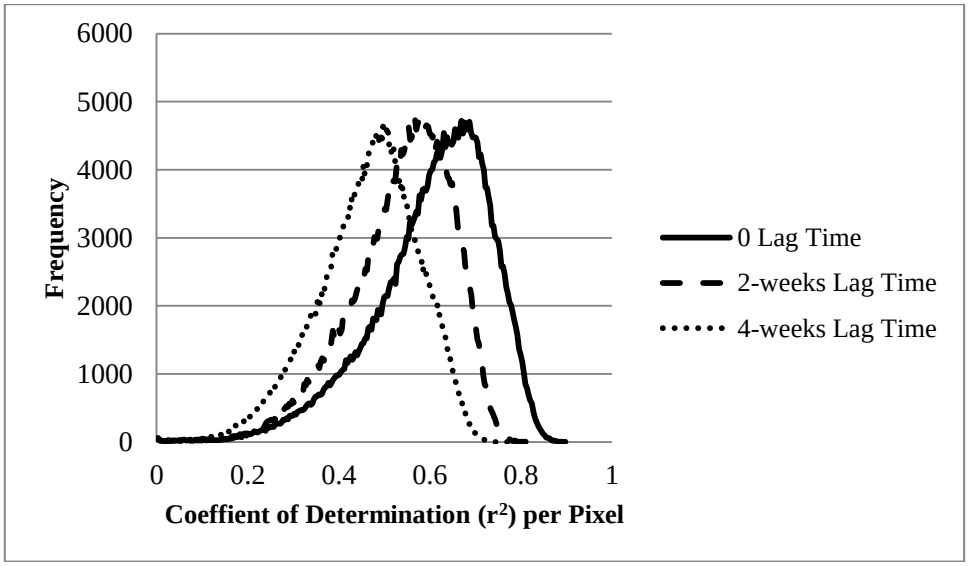


Figure 3. Histograms of pixel values from model results (r^2) for different rainfall lag times.

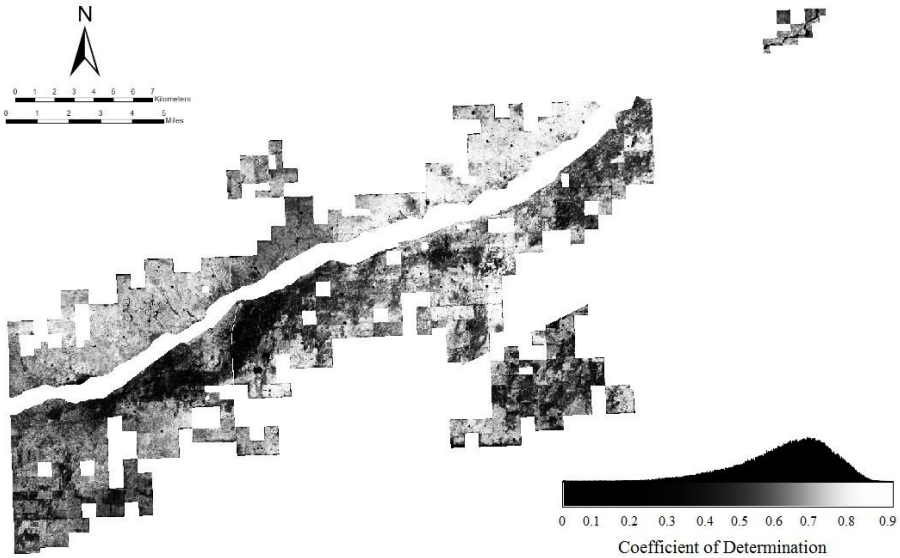


Plate 5. Coefficient of determination (r^2) results per 30-meter pixel from linear regression model using ΔNDVI and cumulative rainfall data between image acquisition dates. Lighter pixels indicate a stronger relationship between the two variables. Results from this model were used to calculate ΔNDVI residuals that were compared to grazing data.

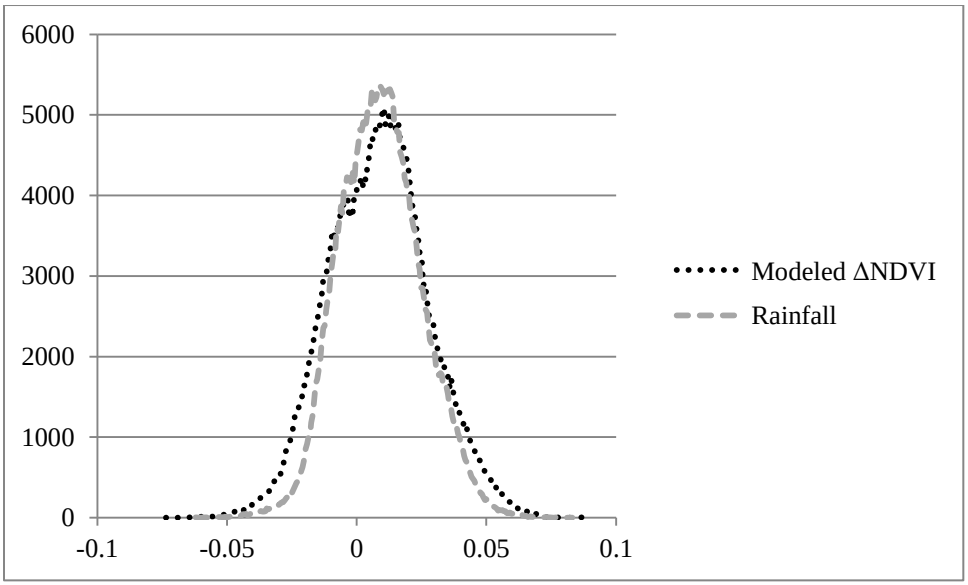


Figure 4. Histograms of results from correlation tests used in model validation. The gray dashed line represents results from the test between residuals and rainfall. The black dotted line represents results from the test between residuals and modelled ΔNDVI.

Modelled ΔNDVI and rainfall data were compared to residuals separately. Both tests yielded negligible results, indicating that there was no heteroscedasticity in the residuals and that a linear regression model between ΔNDVI and precipitation was most

appropriate. The mean image pixel value from the test between modelled values and residuals was 0.008 with a narrow range of values (minimum = -0.07 and maximum = 0.08). The mean image pixel value from the test between rainfall and residuals was also 0.008 with a slightly narrower range (minimum = -0.06 and maximum = 0.08). Results from the F-test indicated that the r^2 values from the model were nearly all significant (mean F = 51.9). With a critical value of 4.17 ($\alpha = 0.05$), 99% of r^2 values were significant. Results from these tests suggested that the model was valid.

One ΔNDVI residual image appeared to have been a statistical outlier (Figure 5, image 1996209 on July 27, 1996) with a mean pixel value that was nearly double that of any other residual image mean. This suggested that the model under estimated the change in NDVI between June 9 and July 27. Upon further investigation, it was determined that the image corresponded to peak NDVI during a drought year. The two images prior to peak NDVI in 1996 had relatively low mean pixel values (mean NDVI = 0.171 and 0.233 for 1996129 and 1996161, respectively). However, the peak NDVI image had values that were much greater (mean NDVI = 0.572). Rainfall for the early part of the year appeared low, but was normal between June and July (immediately before peak NDVI). It is not fully understood what caused the major difference between observed and modelled ΔNDVI for July 27, 1996. It is possible that rainfall variability and other abnormal climatic variables for this year were responsible. The results for this image were not removed from the ΔNDVI residuals time series and these results were used in all further analysis.

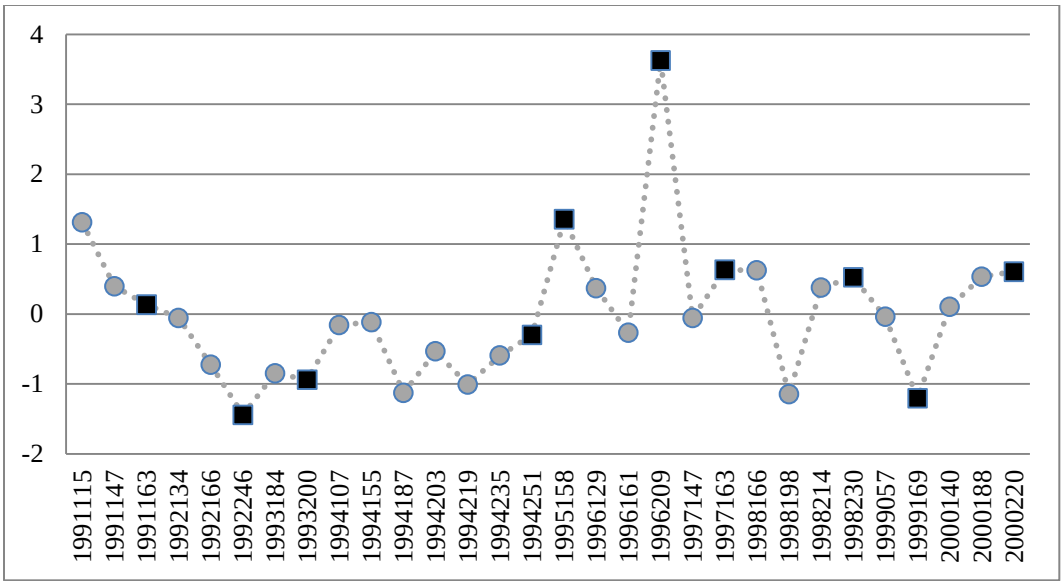


Figure 5. Mean ΔNDVI residuals plotted over time for each date used in the analysis. Black squares represent the last image (peak NDVI) for each year. Values were converted to z-scores prior to being graphed. The image dates (x-axis) are in Julian date format with a four-digit year and three-digit day of the year (e.g. 1997365 = December 31, 1997).

Analysis of the ΔNDVI residuals suggested that there was no significant trend over the course of the study period. There also did not appear to be an intra-annual trend in residuals. Previous studies have looked at trends in NDVI residuals to assess rangeland degradation. However, these data were ΔNDVI residuals, which reflect changes between images instead of years. Further analysis is required to determine if ΔNDVI residuals directly reflect degradation to the study area.

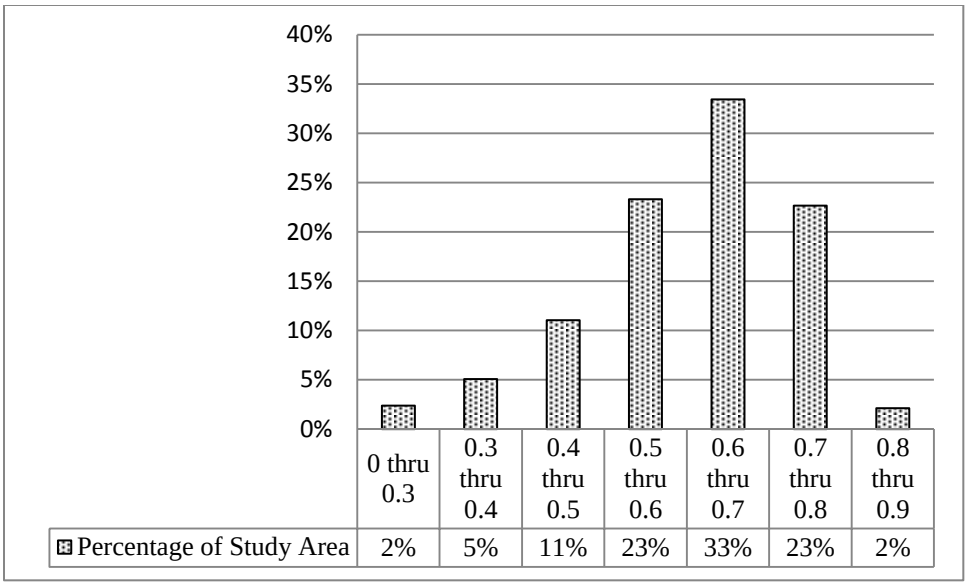


Figure 6. Coefficient of determination (r^2) results per 30-meter pixel as percentages of the study area.

In order to remove the climate signal from ΔNDVI successfully, it was important to model its relationship with rainfall accurately across the study area. Figure 6 above shows that model results were strong for a considerable portion of the study area. The linear regression model yielded r^2 values above 0.5 for over 80% of CNG.

A similar trend in ΔNDVI residuals over the course of each growing season may suggest that residuals represent variability in vegetation vigor due to phenology rather than grazing. Similar intra-annual trends in ΔNDVI residuals were not observed. The limited number of images used for each year complicates this issue, as it is difficult to identify a trend from only two or three images preceding peak NDVI. The lack of similarity in phenology and recent rainfall patterns from Landsat data noted by Evans and Geerken (2004) may have had some effect on ΔNDVI residuals. However, there was no correlation between residuals and the number of days prior to peak NDVI. This does not necessarily indicate differences in phenology had no effect on model results, but it does suggest that these effects were likely minimal in this instance. The graph below illustrates that there was no discernable pattern in ΔNDVI residuals depending on time preceding

peak NDVI. Residuals from this model did not appear to reflect variability in phenology or rainfall patterns.

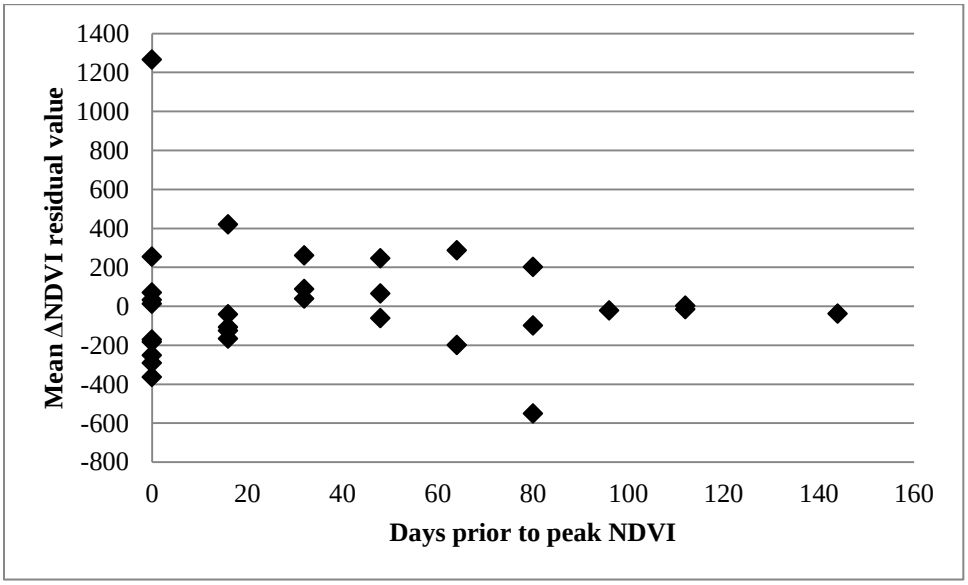


Figure 7. Comparison between mean ΔNDVI residuals and the number of days that the image was acquired before peak NDVI for that year. This graph suggests that there was not an intra-annual pattern in residuals. Images acquired earlier in the season did not appear to trend higher or lower than those later in the season.

		Coefficient of Determination		
Allotment	Acres	Mean	Median	Standard Deviation
Bridge	5956	0.58	0.57	0.11
College	7047	0.53	0.56	0.14
East Artesian	6040	0.61	0.62	0.09
Eighty One	7090	0.65	0.65	0.09
Greenwood	1746	0.64	0.65	0.09
Headquarters	1738	0.63	0.65	0.09
North Lowe	6655	0.73	0.75	0.08
Point	9370	0.67	0.68	0.08
Sandhills	2752	0.65	0.66	0.12
South Lowe	6798	0.65	0.67	0.11
Stateline	4872	0.53	0.55	0.10
Steer	6614	0.56	0.58	0.10
Stevens County	924	0.57	0.59	0.11
West Artesian	6218	0.51	0.51	0.16
Wilburton	8444	0.56	0.58	0.12

Table 3. Descriptive statistics based on coefficient of determination values (r^2) for each of the 15 allotments from the linear regression model between ΔNDVI and cumulative rainfall series with 0-lag time.

5.2 Linear-Log Regression Model

In order to verify that the relationship between rainfall and ΔNDVI was linear, the precipitation time series with a zero-lag time was transformed by calculating the natural log of each dataset in the series. This method did not result in greater r^2 values (mean r^2= 0.344). The mean image r^2 value was far lower than results from the precipitation series that were not transformed (mean r^2 = 0.604). These results suggest that linear regression and not a linear-log regression method was most appropriate for the study area.

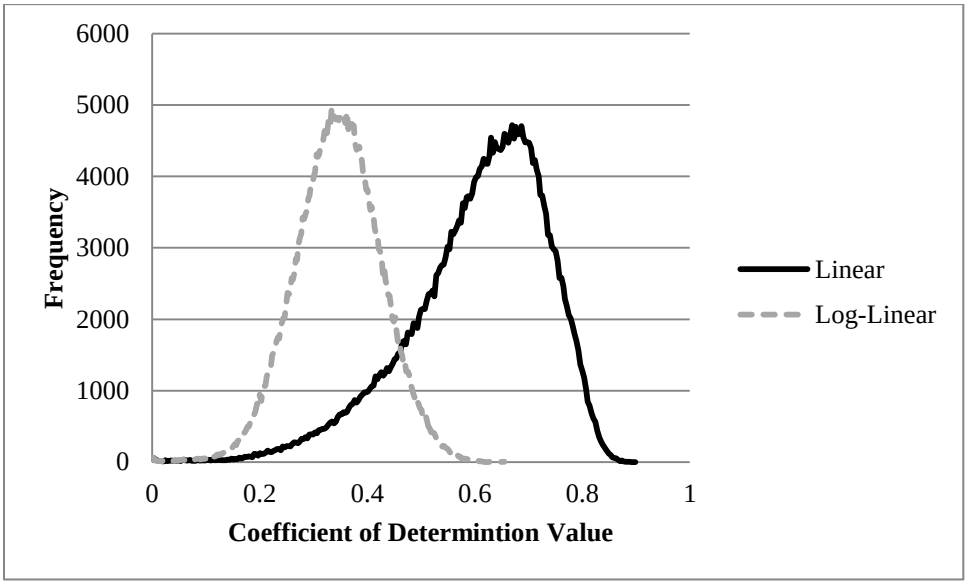


Figure 8. Comparison of results between linear (solid line) and linear-log (dashed line) r^2 model results.

5.3 Correlation Testing

Similar to the linear regression model described above, correlation tests were performed between ΔNDVI residuals and each grazing time series per pixel. The two methods for quantifying grazing data were successful. Both animal units per acre over time and prior grazing day series were negatively correlated with ΔNDVI residuals.

	Animal Units			Grazing Days		
Significance Level	Time between image dates	6-months	12-months	Time between image dates	6-months	12-months
0.005	0%	12%	5%	0%	5%	2%
0.025	0%	27%	26%	0%	27%	17%
0.05	1%	38%	43%	0%	44%	30%
0.1	6%	54%	63%	1%	64%	48%

Table 4. Proportions of the study area where ΔNDVI residuals were significantly correlated with animal units and prior cumulative grazing day series. The columns correspond to each of the six different cumulative grazing series (three series were calculated using animal units and three were calculated using the number of days that grazing took place).

5.4 Animal Units and Residuals

Correlation results between ΔNDVI residuals and cumulative AUD/a corresponding to the times between NDVI image acquisition dates were weak (mean image r = -0.07). There was a moderate negative correlation between ΔNDVI residuals and AUD/a for the previous six-months (mean image r=-0.25). This correlation appeared to be a local phenomenon with some areas having a strong negative correlation (minimum image r = -0.77) and other areas actually having a positive correlation (maximum image r = 0.66). Correlation test results between ΔNDVI residuals and the 12-month cumulative AUD/a series were similar to results from the 6-month AUD/a (mean image r = -0.26, minimum r = -0.66, and maximum r = 0.4).

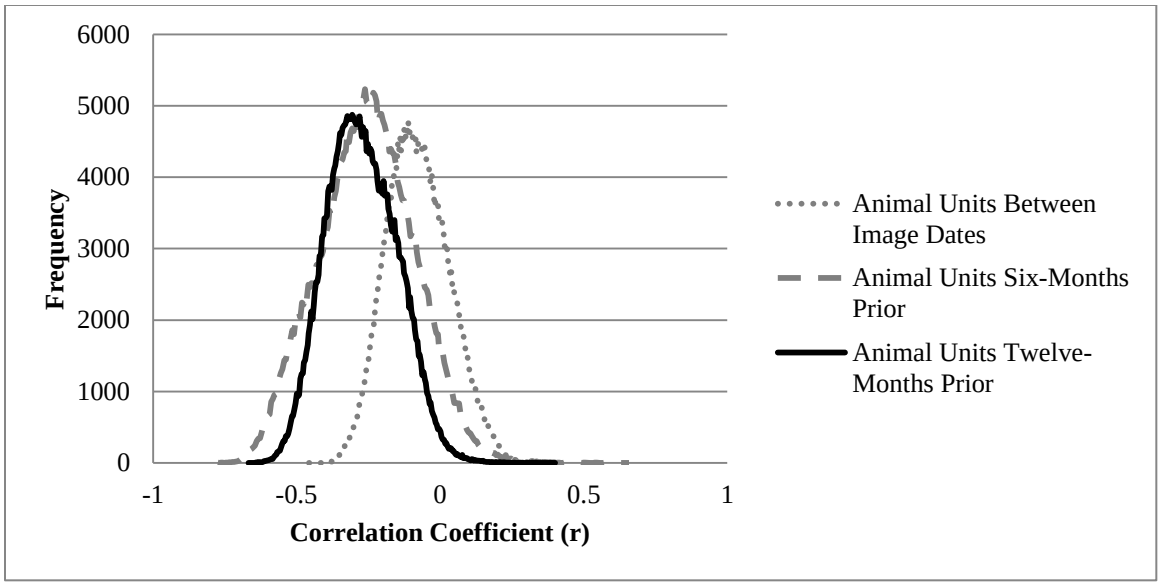
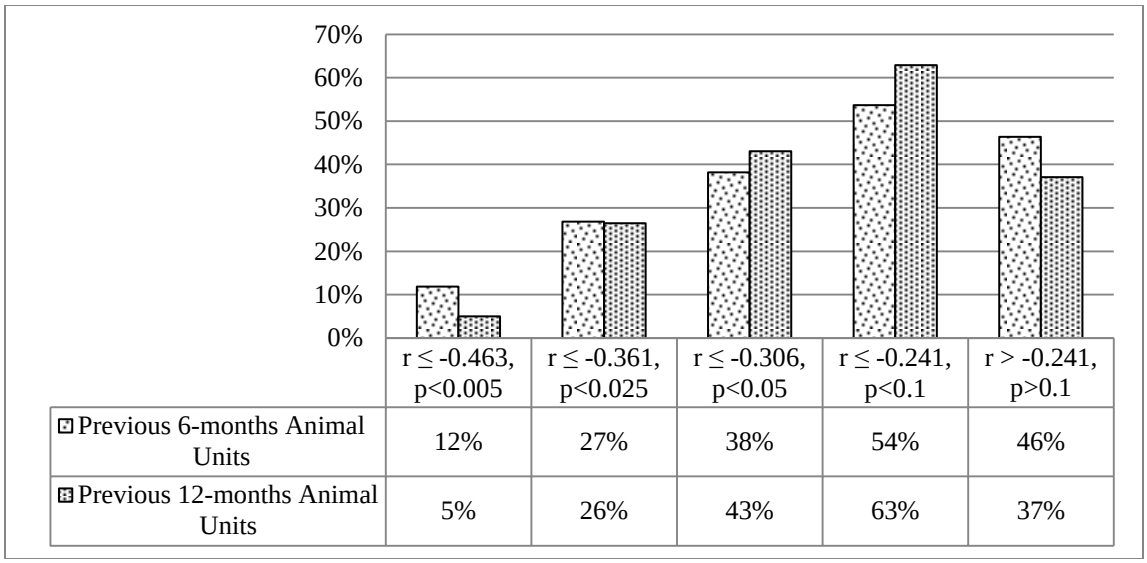


Figure 9. Histogram of pixel values for correlation tests between ΔNDVI residuals and animal grazing units.

A comparison of histograms above illustrates the differences in correlation coefficients between the three AUD/a datasets. For the AUD/a series representing the time between image acquisition dates, less than 1% of the r-values were significant at the 0.05 significance level. Results from the 12 and 6-month grazing series were similar overall, but there were some slight differences. The one-year AUD/a dataset resulted in a higher mean and maximum correlation with ΔNDVI residuals. The six-month AUD/a dataset resulted in a peak frequency that was slightly lower, indicating fewer pixels had a strong negative correlation.



	r ≤ -0.463, p<0.005	r ≤ -0.361, p<0.025	r ≤ -0.306, p<0.05	r ≤ -0.241, p<0.1	r > -0.241, p>0.1
Previous 6-months Animal Units	12%	27%	38%	54%	46%
Previous 12-months Animal Units	5%	26%	43%	63%	37%

Figure 10. Comparison of correlation test results between ΔNDVI residuals and six and twelve-month cumulative animal units. Results are expressed as percent coverage across study area.

5.5 Grazing Days and Residuals

Correlation test results between ΔNDVI residuals and prior grazing days were similar to AUD/a results. The comparison between residuals and grazing days between image dates was very weak (mean r = -0.023). The mean correlation value for the six-month cumulative grazing day series was similar to the twelve-month series (mean r = -0.219 and -0.217, respectively). However, the dataset for six-month grazing days resulted in 64% of the study area having significant r-values at 90% confidence versus 48% for the twelve-month dataset.

Results were very similar between AUD/a and prior grazing days. The cumulative animal units series were a product of prior grazing days (sum of daily animal units per acre × number of days). This suggests that factoring animal units into the correlation tests between grazing days and ΔNDVI residuals did not cause a meaningful change in results. A possible explanation for this is that only the duration of grazing permits and not the number of cattle were modified by land managers in response to forage availability

from year to year. The number of days cattle were allowed to graze each year during the study period was slightly more varied than animal units were (coefficient of variation = 0.21 and 0.17, respectively). However, it is unknown if this apparently subtle difference in variability was likely to have caused differences in results on this scale.

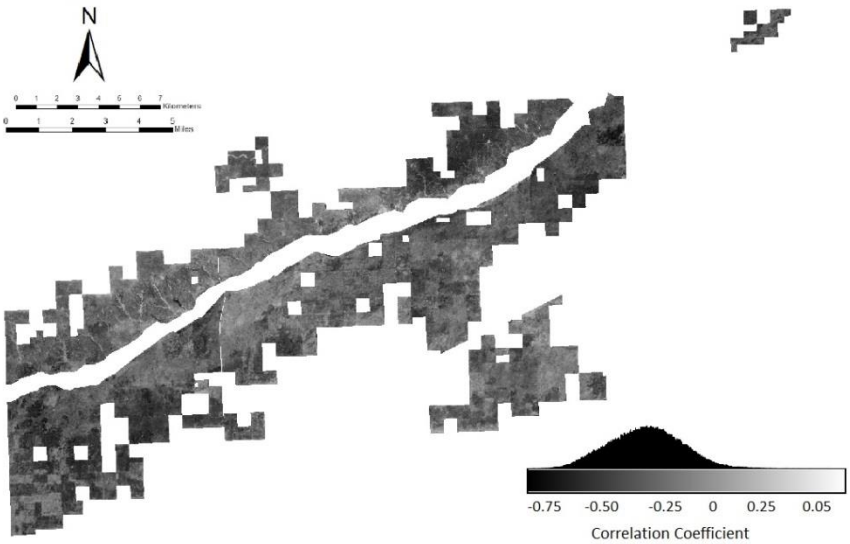


Plate 6. Results from correlation test between ΔNDVI residuals and six-month cumulative grazing day series. Darker pixels indicate a stronger negative correlation between the two variables. The histogram included in the legend indicates a slight negative correlation.

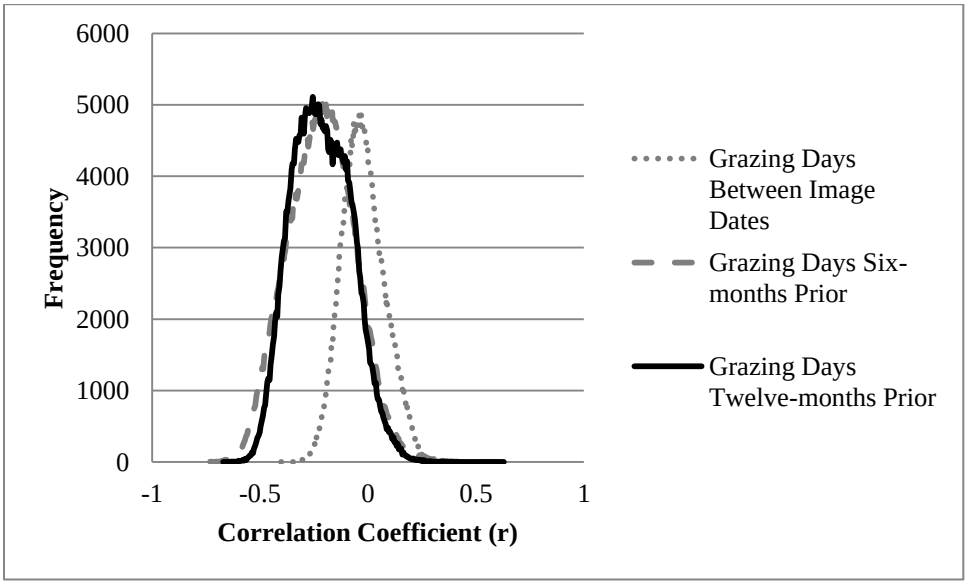
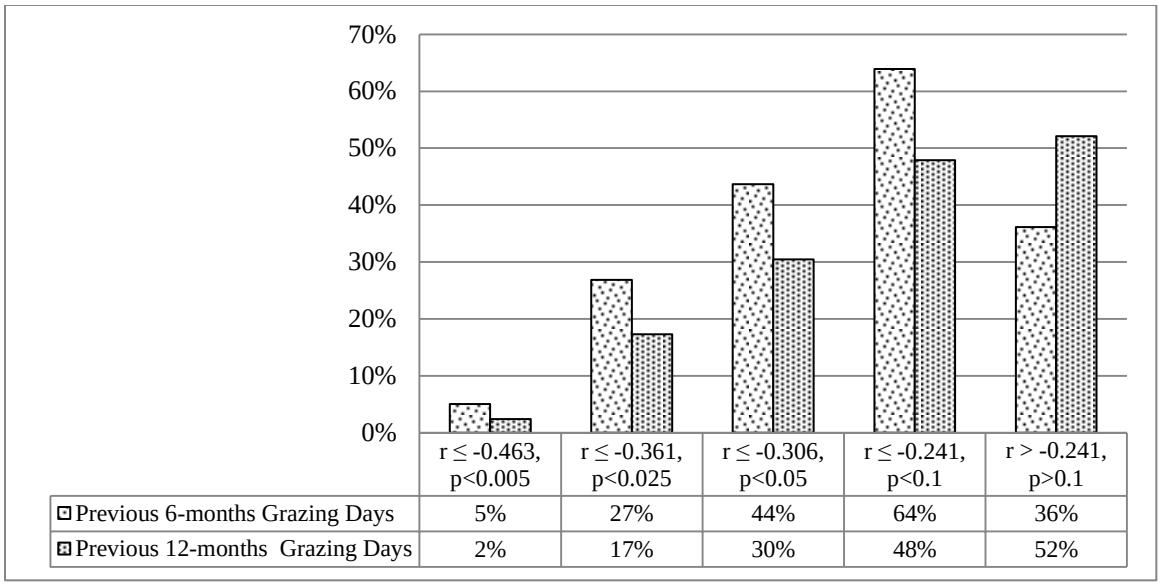


Figure 11. Histograms of pixel values from correlation tests between ΔNDVI residuals and the number of days that grazing occurred prior to image acquisition dates.



	r ≤ -0.463, p<0.005	r ≤ -0.361, p<0.025	r ≤ -0.306, p<0.05	r ≤ -0.241, p<0.1	r > -0.241, p>0.1
Previous 6-months Grazing Days	5%	27%	44%	64%	36%
Previous 12-months Grazing Days	2%	17%	30%	48%	52%

Figure 12. Comparison of percent surface cover for significant correlation test results between ΔNDVI residuals and cumulative six and twelve-month grazing day series.

The correlation between ΔNDVI residuals and grazing data appeared to be strongest in areas where less vegetation would be expected to grow, particularly sand dunes and other places where vegetation was extremely patchy or intermittent. Simultaneously, the results from the linear regression model in some of these areas were still significant, but not as strong. This was expected because variations in vegetation vigor in areas with sand dunes were likely to be more dependent on other variables, such as wind erosion, water runoff, or cattle grazing and trampling. Consequently, vegetation in these areas was more difficult to model using rainfall. Many of the allotments, especially those south of the Cimarron River, contained several small sand dunes with sporadic vegetation cover visible in scenes from the National Agriculture Imagery Program (NAIP) (2014) with one-meter spatial resolution. However, the majority of the sand dunes found on CNG were too small (typically no larger than one pixel) to be differentiated from more vegetated areas with 30-meter Landsat data. In addition, many of these sand dunes were likely to have moved over the course of the study period.

Removal of sand dunes and other areas with sporadic vegetation from the ΔNDVI time series was therefore impractical and undesirable.

There appeared to be little difference between results obtained using the 12 and 6-month cumulative grazing day series (Figure 10). However, the results from these two separate tests did vary spatially. Correlation images calculated using the 12 and 6-month cumulative grazing day series (Plate 7) showed that significant results did not always overlap. Essentially, some areas with a significant correlation in the first test were not significant in the second test and vice versa. In fact, approximately 30% of pixels with significant results from either of the two tests were not significant in the other. The majority of these discrepancies were at the 0.1 confidence level. There was not a perfect overlap between the two sets of results. One possible explanation for this is that the effects of cattle grazing lasted longer in some areas depending on other environmental variables. The correlation test results between ΔNDVI residuals and grazing time accumulated over the previous 12-months appeared to be strongest on three of CNG's 15 allotments (College, Point, and Wilburton). These three allotments had far fewer significant correlation results per pixel between residuals and the six-month cumulative grazing day series.

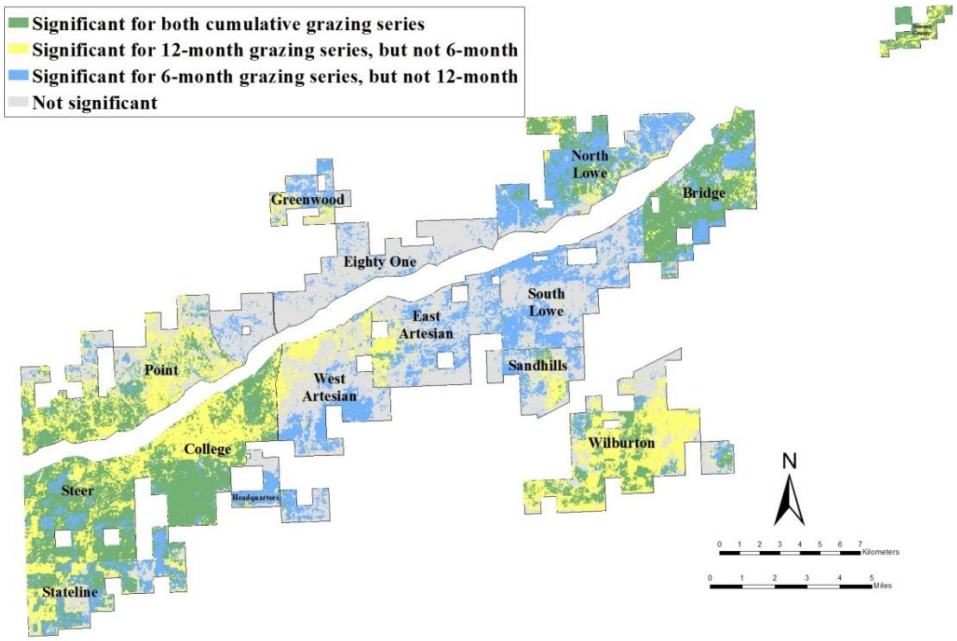


Plate 7. Comparison of significant correlation test results ($p < 0.1$) between ΔNDVI residuals and six and twelve-month cumulative animal units.

5.6 Land Cover Types

Correlation test results were compared to information from the 2001 NLCD (Multi-Resolution Land Characteristics Consortium 2015). The distribution of land cover types varied across the study area.

Allotment	Grassland/Herbaceous	Shrub/Scrub	Other	Total
Bridge	35%	57%	8%	100%
College	64%	31%	5%	100%
East Artesian	36%	57%	7%	100%
Eighty One	58%	32%	10%	100%
Greenwood	72%	24%	4%	100%
Headquarters	87%	8%	5%	100%
North Lowe	43%	45%	13%	100%
Point	59%	33%	8%	100%
Sandhills	51%	46%	3%	100%
South Low	27%	67%	6%	100%
Stateline	92%	3%	6%	100%
Steer	72%	17%	11%	100%
Stevens County	58%	28%	14%	100%
West Artesian	59%	36%	5%	100%
Wilburton	42%	49%	8%	100%

Table 5. Land cover types by allotment based on 2001 National Land Cover Database.

Over 90% of the land cover on CNG was composed of grassland/herbaceous and shrub/scrub (53% and 38%, respectively). Using the Zonal Statistics tool in GRASS GIS, the mean correlation coefficient for each allotment was calculated. Values listed in Table 7 below show that there was little to no difference in ΔNDVI residual/grazing correlation results between the two land cover types. The mean correlation coefficients for the two primary land cover types in total were also very similar (r = -0.22 and -0.21, respectively). In sum, there was clearly some variability in results between allotments, but there did not appear to be substantial differences between land cover types within each allotment.

	Mean Correlation Coefficient		
Allotment	Grassland/Herbaceous	Shrub/Scrub	Other
Bridge	-0.35	-0.34	-0.31
College	-0.30	-0.25	-0.19
East Artesian	-0.16	-0.20	-0.16
Eighty One	-0.10	-0.13	-0.13
Greenwood	-0.19	-0.18	-0.18
Headquarters	-0.25	-0.13	0.28
North Lowe	-0.32	-0.32	-0.27
Point	-0.16	-0.21	-0.16
Sandhills	-0.19	-0.15	-0.08
South Lowe	-0.22	-0.22	-0.07
Stateline	-0.27	-0.20	-0.24
Steer	-0.34	-0.31	-0.32
Stevens County	-0.31	-0.31	-0.32
West Artesian	-0.16	-0.10	-0.04
Wilburton	-0.16	-0.15	-0.12

Table 6. Mean correlation coefficients between ΔNDVI residuals and 6-month cumulative grazing day series for each land cover type by allotment. There was clearly some variability in results between allotments, but there did not appear to be substantial differences between land cover types within each allotment.

5.7 Soil Types

Areas south of the Cimarron River, which were identified as having sandy soils, tended to contain stronger negative correlations between ΔNDVI residuals and grazing data. Allotments north of the river, identified as having loamy soils, tended to have

weaker correlations. However, Ulysses silt loam soil, found north of the river exclusively, had the strongest negative correlation (mean r = -0.3). This was the only soil type found in the north with a mean correlation value that was stronger than any of the soil types found in the south (Plate 4).

Using results from the correlation test between ΔNDVI residuals and six-month cumulative grazing day series, pixel values corresponding to areas within the boundary of each soil type were averaged. Mean correlation values for each soil type did not appear to isolate local areas that had a strong relationship completely. None of the 12 soil types on CNG corresponded spatially to the strongest correlation test results exclusively; all of the soil types included some weak and some strong r-values. In total, all of the loamy soils north of the Cimarron River yielded weaker results than those to the south with sandy soils, with the exception of Ulysses silt loam.

Soil Type	**Percent Coverage over study area**	**Mean Correlation Coefficient (r)**	**River Bank**
Ulysses silt loam	2.90%	-0.30544	North
Eva-Optima loamy fine sands	15.80%	-0.25681	South
Dalhart loamy fine sand	15.40%	-0.2498	South
Dalhart-Eva Loamy Fine Sand	2.20%	-0.2372	South
Bigbow loamy fine sand	1.50%	-0.21288	South
Optima loamy fine sand	16.10%	-0.21116	South
Eva loamy fine sand	18.80%	-0.21106	South
Atchison loam	12.40%	-0.18831	North
Atchison clay loam	4.60%	-0.18322	North
Atchison-Rock complex	3.50%	-0.17932	North
Richfield silt loam	1.80%	-0.16983	North
Wagonbed silty clay loam	3.80%	-0.14414	North

Table 7. Soil types found on CNG with respective mean correlation coefficient found for each. The mean correlation coefficient was calculated from results between ΔNDVI residuals and six-month cumulative grazing day series.

Chapter 6 Discussion

The ΔNDVI-precipitation model revealed that there was a strong relationship between the two variables (r^2= 0.6-0.89) across 60% of the study area. The strength of the model was an important factor in calculating ΔNDVI residuals that could be correlated with cattle grazing figures. Based on the F-test, it was determined that over 95% of the study area contained significant coefficients of determination ($p \leq 0.05$). Correlation tests, one between the residuals and rainfall and another between the residuals and modelled ΔNDVI, yielded negligible results. This indicated the residuals were not dependent on variability in rainfall. Changes in NDVI between images appeared to have been modeled accurately.

Previous research conducted in Kansas has shown that a lag time in rainfall is required to model NDVI accurately (Wang et al. 2005). However, results presented in this paper suggested that a zero lag time in precipitation was most appropriate; in fact, the results worsened as lag times increased. The reasons for this difference were beyond the scope of this study.

Results indicated that there is a moderate negative correlation between grazing time and changes in vegetation vigor in some areas. This suggests that cattle grazing did have a measurable effect on CNG and that changes in NDVI not explained by rainfall were related to land use. However, the correlation was weak in some areas. There were a number of limitations to this study that require further research and improvements in methodology to be fully addressed. The coarse temporal resolution of Landsat data reduced the NDVI sample size (n=30). Conversely, the 30-meter spatial resolution allowed for grazing allotments to be analyzed on a local scale, something that would not

have been possible with satellite data having a spatial resolution of several hundred meters (e.g. AVHRR or MODIS).

Results from this study were successful in showing that a relationship does appear to exist between ΔNDVI residuals and cattle grazing. A considerable portion of the study area showed a stronger negative correlation between cattle grazing and residuals than NDVI and ΔNDVI (Appendix I). As previously noted, significant correlations appeared to be local occurrences and some areas did not yield significant results. A number of other environmental variables (e.g. dominant vegetation types or prior degradation) cannot be ruled out as potential causes. Maps of dominant grass species or past overgrazing in different areas were not available. These and other variables could have caused different responses to grazing pressure. The length of time that grazing effects may persist could also be dependent on other environmental variables, which would suggest that results based on a series of grazing data should be used to test this. In sum, ΔNDVI residuals yielded a stronger negative, but moderate, correlation with grazing time.

Unlike the present study, Wessels et al. (2007) and Wessels et al. (2012) applied a logarithmic transformation to their precipitation data prior to developing their NDVI models. Their method assumes that vegetation responses to rainfall may be non-linear in that as it increases it has less of an effect on NDVI; this is most likely a valid assumption in wetter regions. When a logarithmic transformation was applied here, it resulted in lower r^2 values, suggesting that soil on CNG is rarely wet enough for their assumption to hold.

Further research is needed to ascertain what factors play a role in the correlation between ΔNDVI residuals and when cattle are introduced. Cattle are generally present on CNG at the same time each year, thereby making it difficult to determine which point in the growing season the introduction of cattle has the greatest effect on NDVI. Unfortunately, very few studies that analyzed NDVI residuals to assess rangeland degradation have been conducted in areas where quantifiable grazing information was available.

As in this study, Archer (2004) converted the number of cattle to animal units prior to comparing grazing data to residuals. Like Archer (2004), this study also found that a significant correlation existed only between stocking duration and not animal units. The limitations associated with using animal units to measure grazing likely affected correlation test results. The AU factors for average sized cattle were used in this study because it was impossible to determine the size of cattle based on grazing permit data. Due to the general make up of such data, i.e. a simple quantity of animals, very little can be attributed to per head consumption. Due to a range of variables including the size of each cow and the age of each calf, a simple AU factor proved less meaningful than grazing duration.

The variability in recovery time from grazing could provide rangeland managers valuable information concerning fallow periods and how to ensure that each allotment is given an appropriate amount of time to rest each season. Cattle are typically introduced on May 1 each year. This is a largely arbitrary date in late spring. Calculating ΔNDVI residuals earlier in the season would indicate when grasses have adequately recovered from the previous year's grazing. It may be possible for the grassland as whole or for

allotments individually to recover from the previous year's grazing impacts earlier or later than May 1. The arbitrary May 1 introduction date is not always the date grazing permits start. Introduction times were often postponed days or even a few weeks past May 1 during years with limited rainfall and low forage availability. In fact, 1996 was a drought year and grazing was only permitted from day to day depending on conditions. With the additional information about optimum fallow periods that can be obtained using methods outlined in this paper, land managers on CNG could potentially be able to make timely decisions based on data covering the entire grassland.

The majority of land on three allotments (College, Point, and Wilburton) were found to have far more significant correlations between residuals and the 12-month cumulative grazing series than the six-month cumulative series (Plate 7). Perhaps these three allotments carry a longer response time to grazing than others and require longer fallow periods. More information, including in situ measurements of phytomass per unit area, would be required to test this hypothesis. Several different cumulative grazing times would need to be calculated and compared to residuals individually to identify the strongest correlation for each allotment. This method would be similar to that used by Evans and Geerken (2004) to determine the best accumulated rainfall lag time. Ultimately, this would create a new application for the residual trend method by assessing the effects of grazing based on records to determine the length of time in which these effects remain.

The residual trend method cannot detect dominant vegetation change from palatable to non-palatable vegetation. However, the processes that would cause a change in vegetation appear unknown. Results from this study show that vegetation change of

this type may be far more complicated than simple over consumption of fodder. Many of the dominant grass species on CNG are thought to increase with overgrazing (Table 1). This fact, coupled with results that show a negative correlation between ΔNDVI residuals and the cumulative grazing day series, appears to suggest that trampling and soil compaction by cattle also adversely affects vegetation growth. More research is needed to validate this theory, but it is possible that the less palatable grass species listed in Table 1 are also better adapted to compacted soils.

There did not appear to be a difference in results depending on land cover type. The 2001 NLCD was based primarily on two very broad cover types. It is likely that these data were simply too coarse to yield meaningful results. More data are needed to identify if and where grazing pressure may covary with different land cover types. Additionally, earlier NLCD data that coincided with the initial part of this study period were not at all useful as only one land cover type was identified across the entire study area. Analysis that is more meaningful will likely require land cover data classified into narrower categories distinguishing between different types of grasses.

Soil data were on a slightly finer scale than land cover. There appeared to be a slight difference in results between sandy and loamy soils. However, this was not always the case. Areas with Ulysses silt loam soil had the strongest mean correlation between ΔNDVI residuals and grazing data. These areas were all north of the river and surrounded by soils that corresponded to areas where residuals/grazing correlation test results were weak. It is likely that variability in soil type, much like vegetation type, cannot be used to explain these results because significant differences are only discernible on a much larger scale. Although there were unique differences between each of the soil types analyzed,

there may not have been enough variability to affect results. Changes in results would likely be observable on a statewide or regional level as opposed to the county level, which was the case for this study.

The residual trend method must be used on the pixel level to work properly. Previous studies have assumed that other variables that could affect vegetation growth will not vary significantly at the pixel level on a decadal scale (e.g. Paudel and Anderson 2010; Wessels et al. 2007). However, this may not always be true. For example, it is likely that many of the sand dunes on CNG did move given the fact that the area is semiarid and frequently subjected to strong winds. Another variable the method might not have been able to negate is variability in rainfall timing. Heavier rain early or later in the season could conceivably affect vegetation growth and cause less predictable changes in NDVI. An example of this was from the 1996 imagery, where there was little rainfall early in the season and average rainfall immediately prior to peak NDVI. The change in vegetation immediately leading up to peak NDVI was much greater than the model estimated and it is likely that rainfall timing and not simply rainfall played a significant role in the under prediction of ΔNDVI for 1996. Finally, degradation carryover from previous years most likely affected vegetation growth in subsequent years. This carryover effect is likely the most important of all future research needs suggested in this report because it may assist land managers in determining optimum fallow periods for each allotment.

Multiple ΔNDVI images from each growing season were modelled. Changes in NDVI between images may not always reflect the total biomass produced over the course of one growing season. Consequently, results presented here cannot be interpreted as

indicators of degradation from year to year. The slope and intercept of the model used in this study are likely to be different from those calculated using net annual vegetation growth. These results suggest that as grazing intensity increases, vegetation regrowth is inhibited. However, the decline in regrowth was measured over a short period and cannot be extended to net annual degradation.

Chapter 7 Conclusion

Rangeland degradation is a complex phenomenon dependent upon several variables and differentiating its causes is difficult. The purpose of this paper was to evaluate the effects of cattle grazing on Cimarron National Grassland and to identify ways in which the residual trend method could be applied to Landsat data. According to the results, it is possible to model vegetation growth based on rainfall using Landsat TM data accurately. Several different measures of grazing intensity were compared to ΔNDVI residuals, ΔNDVI, and NDVI. Results from the correlation tests were not definitive, but they did appear to show that there was a moderate relationship between residuals and grazing data. All of the correlation tests between residuals and grazing data yielded correlation coefficients that were mostly negative or close to zero. Results confirmed that using the residual trend method with ΔNDVI removes the climate signal and amplifies that from human-induced degradation.

This project differed from previous research that used the residual trend method in several ways. The size of the study area was relatively small (82,000 acres) and scattered across 15 separate allotments. The level of anthropogenic degradation was not expected to be strong. Landsat data with a 30-meter spatial resolution and 16-day revisit time were used. Vegetation change (ΔNDVI) was used to calculate residuals instead of NDVI. Finally, precipitation between image acquisition dates was summed for each observation instead of using the best correlated cumulative lag times for each pixel. Nevertheless, the underlying theory and goals of this study were the same as other studies that used the residual trend method, removal of the climate signal from remotely sensed vegetation

time series. This paper has demonstrated that the methods outlined above can successfully remove the effects of rainfall from ΔNDVI.

There was a strong correlation between ΔNDVI and precipitation. Using ΔNDVI as opposed to actual NDVI proved valuable as it provided a much simpler way of calculating the precipitation inputs for the model. The model was evaluated to ensure the assumption of no heteroscedasticity in the residuals was not violated. An F-test also revealed that r^2 results from the model were significant at the 95% confidence level. Correlation tests revealed that there was a moderate negative relationship between ΔNDVI residuals and grazing duration each year. Interestingly, there did not appear to be a strong relationship between animal units and ΔNDVI residuals. The strength of the relationship between residuals and grazing time varied across most of the allotments. There did not appear to be a relationship between results and land cover types. Higher correlation values did appear to correspond with sandy soils, especially with those in the southwest of CNG.

In spite of not finding evidence to suggest that overgrazing occurred on CNG in the 1990s, this study has shown that there was a relationship between ΔNDVI residuals and grazing activity. Possible declines in net productivity from year to year were not assessed, but results do provide a good indication of how grazing duration can affect vegetation growth. Responses to grazing intensity over different time scales varied spatially. This suggests that different parts of the study area were affected by grazing duration differently. There appeared to be a carryover in grazing response that may have been influenced by the degree of prior degradation based on the observation that areas

with lower, but still significant, r^2 values tended to have residuals that were best correlated with the six-month grazing series.

It is not fully understood how grazing data should be summed over time. Exploration of additional cumulative grazing times could provide insight into the relationship between grazing and residuals. The amount of time it takes grasslands to recover from grazing relates to optimum fallow periods and thus warrants further investigation. This would also require further research into the effects of cattle introduction times. Improvements to methods for calculating the optimum grazing series would allow future research to evaluate the importance of cattle introduction times. Variability in when grasses begin to grow each year and the rate in which they mature depending on rainfall would likely make the introduction of cattle on the same date each year (typically May 1 for CNG) undesirable.

The correlation tests between ΔNDVI residuals and stocking information did not yield exceptionally strong r-values. However, results from these tests were far stronger than results from correlation tests where NDVI or ΔNDVI were used. It is likely that additional variables other than grazing were also attributable to variability in vegetation growth. Nonetheless, ΔNDVI residuals do appear to represent a general measure of effects cattle grazing can have on grasslands in semiarid environments. Further research is needed to determine the best method for aggregating grazing data.

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Appendix I Comparison between NDVI, ΔNDVI, and Grazing

Correlation tests were run between the number of six-month cumulative grazing day series and ΔNDVI and NDVI, both vegetation datasets individually. Results from these tests suggested that there was a stronger correlation between grazing figures and the residuals than between grazing figures and NDVI or ΔNDVI (mean correlation r = 0.14 and -0.12, respectively). Less than 1% of the negative correlation test results between NDVI and grazing figures were significant (Figure 14). The test between ΔNDVI and grazing figures resulted in mostly negative, but not significant, correlations across CNG. Both NDVI and ΔNDVI image results had distributions that were clearly peaked with the majority of results centered on the mean and a relatively narrow distribution (Figure 13).

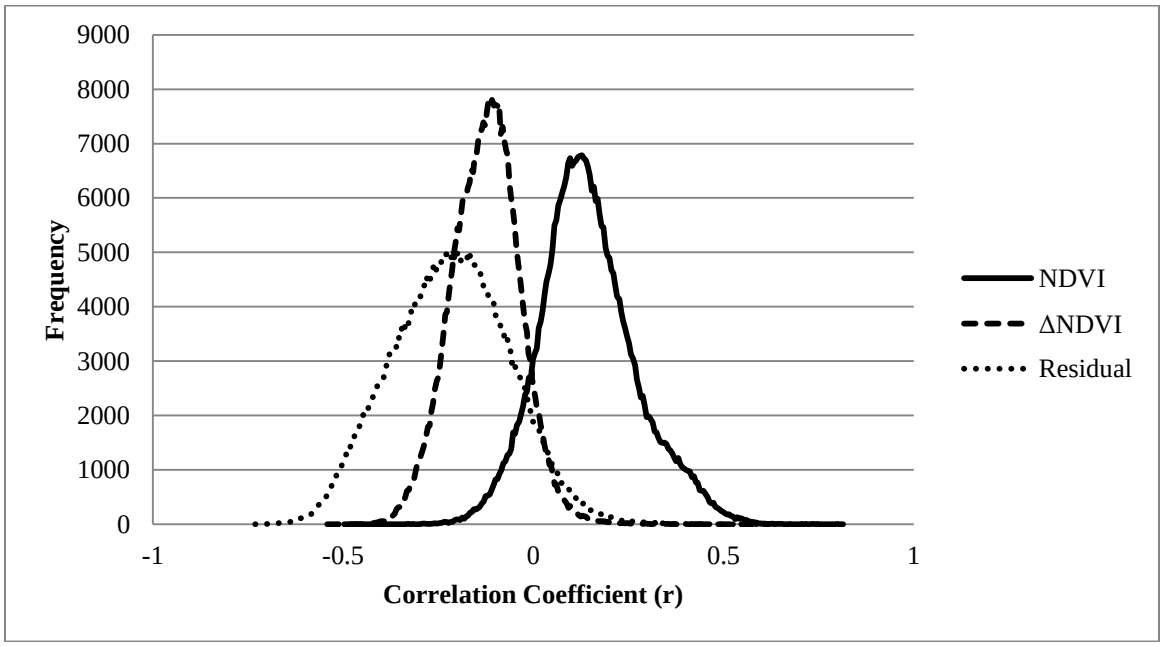
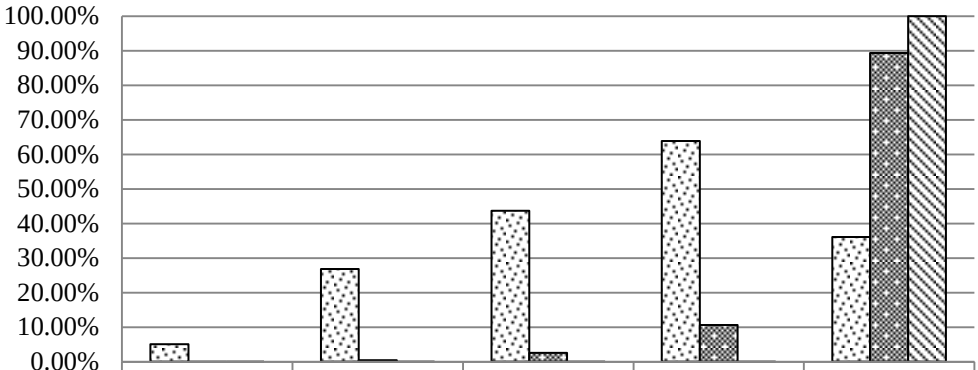


Figure 13. Frequency graphs comparing correlation coefficients calculated per pixel between six-month cumulative grazing day series (x) and NDVI (solid black), ΔNDVI (dashed black), and ΔNDVI residuals (dotted black). Each y variable was compared to the x variable individually in a separate test.

There was clearly some overlap between results from all of the above correlation tests (Figure 13). The residuals had the strongest correlation with cattle grazing practices on CNG. The percentage of significant correlation results from the residuals was over 17

times greater than those for ΔNDVI. The residual trend method, when used to analyze ΔNDVI, does appear to remove the climate signal and provides a measure of vegetation variability correlated with human agency.



	r ≤ -0.463, p<0.005	r ≤ -0.361, p<0.025	r ≤ -0.306, p<0.05	r ≤ -0.241, p<0.1	r > -0.241, p>0.1
ΔNDVI Residuals	5.02%	26.84%	43.67%	63.89%	36.11%
ΔNDVI	0.00%	0.41%	2.50%	10.65%	89.35%
NDVI	0.00%	0.01%	0.02%	0.06%	99.94%

Figure 14. Comparison of significant results as a percentage of the study area from correlation tests between the previous six-month cumulative grazing day series and ΔNDVI residuals, ΔNDVI, and NDVI. The percentage of results that were not significant at the 90% confidence level was included in the far right column.