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MONITORING CHANGES ON THE SHEYENNE NATIONAL GRASSLAND USING
MULTITEMPROAL LANDSAT DATA

By

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Bachelor of Science, University of Minnesota – Twin Cities, 2010

A Thesis

Submitted to the Graduate Faculty

of the

University of North Dakota

In partial fulfillment of the requirements

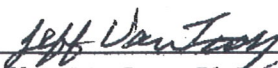
For the degree of

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This thesis, submitted by Stefano Marano Potter in partial fulfilment of the requirements for the Degree of Master of Science from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.



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Dean of the School of Graduate Studies



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ABSTRACT

Tallgrass prairies are one of the rarest ecosystems on the planet as up to 99% of their historical extent has been converted to agriculture. Once a prairie is converted there is often a loss of ecosystem services such as soil retention, carbon storage, water quality and a loss of biodiversity. It can take centuries to restore a native prairie after conversion has taken place. The Sheyenne National Grassland is managed by the U.S. Forest Service and contains the largest publicly owned tract of tallgrass prairie remaining in North America making it a highly valuable for conservation.

Ordinary least squares regression was implemented to evaluate statistically significant trends at a per pixel basis in selected Vegetation Indices (VI) between the years of 1984 and 2011 on the Sheyenne National Grassland. VIs included NDVI, NDII RGR and SWIR32. Additionally, a Composite Index which sought to combine information from the original four indexes was created to evaluate the usefulness of combining indexes. A random forest regression model was also used to evaluate which independent variables were the most useful in predicting VI values through time.

Between 1984 and 2011 the NDVI and NDII have increased while the RGR and SWIR32 have decreased. This indicates that greenness and wetness have increased through time while stress and non-photosynthetic vegetation have decreased. It is likely that the increase in NDVI is driven by a complex relationship between the influence of climate change and cattle grazing on the relative abundance of C₃ and C₄ plants. It is hypothesized that continuously stocked cattle grazing has reduced the vigor and competitive ability of native C₄ grasses which competitively releases C₃ grasses that are more tolerant of grazing and are primarily invasive. In addition to the competitive release of cattle grazing, C₃ establishment is promoted through increased spring precipitation which has increased over the last century.

CHAPTER I

INTRODUCTION

Tallgrass prairies are the most productive grasslands found in North America and once occupied up to 60 million ha of land in the U.S. However, now only 2.5 million ha remain largely because of agricultural expansion. This makes the tallgrass prairie one of the most decimated ecosystems on the planet (Flores, 1996; Knapp & Seastedt, 1998). Once a prairie is converted to agriculture (or any other land use) it takes centuries to restore. Additionally, replacement of tallgrass prairie with agriculture often results in increased soil erosion, reduced water quality, loss of biodiversity, and reduced carbon storage. For example, 330 of the 435 species of birds which breed in the U.S. breed in the Great Plains. Between 1969 and 1991 declines of up to 48% have been estimated due to loss of habitat. Prairie dogs play a critical role in nutrient cycling and soil formation but populations are estimated to have declined by 98% since European settlement due to competition from cattle for forage (Samson and Knopf 1994).

During the 1930's when large areas of prairie were being converted to agriculture few recognized the ecological sensitivity of the Great Plains and the importance they played in holding soil together. Without native grasses to keep the soil in place widespread wind erosion occurred which carried away top soil and reduced the ability of farmers to produce crops.

Because so much of the original extent of tallgrass prairie has been lost, the conservation of the few remaining tracts has become increasingly important to conserve the ecosystems and the species they contain (Sampson and Knopf, 1994).

The Sheyenne National Grassland (SNG), managed by the U.S. Forest service, is located in southeastern North Dakota, and at 28,000 ha it is the largest remaining publicly owned tract of tallgrass prairie and oak savannah in North America. The SNG is one of the most diverse landscapes in North Dakota and is home to numerous sensitive species and one endangered species. It is far from pristine though as invasive forbs and grasses are present, trees have expanded due to fire exclusion, and overgrazing has likely influenced species compositions. Major management issues on the SNG include infestation by leafy spurge (*Euphorbia esula*) and Kentucky bluegrass (*Poa pratensis*), reduction in native warm season grasses, invasion of trees and lack of residual vegetation for wildlife, prescribed fire and livestock forage (Svingen, Braun, and Gonzalez 2008). These changes are likely influencing ecosystem function and it is important for land managers to be able to identify locations where changes in ecosystem condition have taken place, and to determine why potential changes have occurred so that management action can be better informed and prioritized.

Due to its large size it is expensive and difficult to assess the health of the SNG by conducting field surveys alone, but it is possible that satellite sensors (i.e. by remote sensing methods) can provide valuable information about ecosystem health to land managers. Remotely sensed vegetation indices (VI's) have the potential to provide information about functional indicators of grassland states (Hill et al. 2013). For example, it has been shown that VI's such as the Normalized

Differenced Vegetation Index (NDVI) which acts as an indicator of photosynthesis, the Carotenoid Reflectance Index I (CRI1) which is sensitive to yellow pigments, the Anthocyanin Reflectance Index (ARI1) which is sensitive to stress, the Red Green Ratio (RGR) which is also sensitive to stress (but less than ARI1), the Normalized Difference Infrared Index (NDII) and Short Wave Infrared Ratio (SWIR32) which is sensitive to non-photosynthetic vegetation can be used to differentiate between grassland states across a number of prairie types in North America (Hill 2013).

Evaluation of VI's from multi-temporal imagery may be particularly useful to evaluate how spatial variation in grassland quality has changed through time, and the release of the Landsat archive in 2008 has made it easier to conduct analysis dating back as far as 1972 when the first Landsat sensor became operational.

Numerous studies have evaluated temporal trends in VIs and band reflectance from time series of satellite imagery using ordinary least squares regression (Kennedy, Cohen, and Schroeder 2007; Kennedy, Yang, and Cohen 2010; J. E. Vogelmann, Tolk, and Zhu 2009; James E Vogelmann et al. 2012; Röder et al. 2008), but these studies have primarily focused on forested ecosystems and the evaluation of just one or two indices such as NDVI and SWIR32. These studies have also only examined how a VI might be changing through time, and not explored the relationship between VI signals and climatic factors such as precipitation and temperature. Additionally, these studies have not evaluated how regression results vary by segmenting images by different parts of the growing season (e.g. May vs. August) which may be useful to assess how spatial locations vary due to phenology.

One of the strengths of using regression of VIs against time as a change detection approach is that spatial evaluation of trends can be assessed by fitting regression models to each individual pixel in a study area over the desired time frame. Significance of the regression fit can then be assessed by evaluating probability of the F-statistic (the p-value), overall fit by assessing R^2 values, and magnitude of change by assessing slopes (James E Vogelmann et al. 2012). Further insight can be drawn by incorporating ancillary data which describes the vegetative composition of individual pixels, and then stratifying regression results by the different vegetation communities and comparing differences (J. E. Vogelmann, Tolk, and Zhu 2009).

More recently, decision trees such as random forest models have also been found to be useful in remotely sensed studies to classify land cover. A primary advantage in implementing random forest models is that differences in feature importance between many independent variables can be assessed by calculating which independent variable provided the most information to the model (Kulkarni and Lowe 2016; Rodriguez-Galiano et al. 2011). In this way, random forest models may also be useful in change detection studies by evaluating which independent variables may provide the most important information as to the cause of a change in a VI value. When used in conjunction with a simple linear regression the feature importance should then theoretically align with R^2 values for specified independent variables.

Study Objective

Due to the uniqueness of the Sheyenne National Grassland as the largest publicly owned tallgrass prairie remaining in North America it has tremendous conservational value. Despite its designation as a national grassland it faces numerous ecological threats from invasive species, fire exclusion and overgrazing. The large size of the grassland make it difficult to use field methods

alone to assess health, and remote sensing has potential to provide important insight. Detailing specific locations which have undergone historic change, and continuing to analyze how conditions change in the future can provide important information to land managers to help prioritize field surveys. The goal of this study was to evaluate a time series of remotely sensed images acquired from Landsat 5 between 1984 and 2011. VI's including NDVI, NDII, RGR and SWIR32 were calculated for all images in the time series (79 images in total) between the months of May and September. VI's can be used as functional indicators of ecosystem health. Additionally, a fifth index which sought to combine all four original indexes was created to determine if VI's could be integrated to simplify the process. Simple linear regression was evaluated through the time series by using VI values per pixel as the dependent variable and time as the independent variable to determine if significant trends in VI values occurred. Additionally, it was of interest to determine if climate and management were influencing VI trajectories, and therefore antecedent precipitation, antecedent growing degree days, and grazing pressure was also evaluated with simple linear regression as independent variables. Regressions were evaluated through the entire time series, and three separate segmentations of the growing season such as images acquired in the Early Season, the Peak Summer and the Late Season.

Multiple regression was also used to evaluate how much of the total variation per pixel could be explained with the selected independent variables by comparing adjusted R^2 values. Additionally, random forest regressions were used to evaluate feature importance of independent variables. Lastly, comparisons of regression which were stratified by unique landforms and species compositions were compared to evaluate differences in trajectories.

Objectives of this research were to:

1. Use simple image differencing to determine if a change in VI values have occurred through time.
2. Implement simple linear regression models to determine how VI values may have changed due to independent variables such as time, climate, and grazing pressure.
3. Determine if there is spatial variation in change across landforms and species compositions.
4. Evaluate the capability of a random forest regression to predict index values based on the included independent variables.
5. Explore the capability of combining original indexes into a single new index to act as an indicator of vegetative state.

CHAPTER II

LITERATURE REVIEW

Ecological Importance of Grasslands

Grasslands occupy approximately 37% of Earth's land surface (O'Mara 2012) are one of the most biologically productive of all ecosystems (Williams and Diebel 1996) and in North America are among the most at risk resources on the continent (Samson, Knopf, and Ostlie 2004).

Due to the high productivity of their soils, land use change, and more specifically conversion to cultivated (on the most productive lands) or grazed land (on more marginal lands), has led to poor conditions and degradation for many of the world's grasslands which threatens their ecosystem function (Sala and Paruelo 1997; Fore, Overmoe, and Hill 2013; O'Mara 2012). Ecosystem services provided by grasslands include soil conservation, nutrient retention, biochemical recycling, wildlife habitat, forage, maintenance of biodiversity, and food production (White, Rohweder, and Murray 2000).

The world population is around seven billion people today, and is projected to eclipse 10 billion by the end of the century. With this population growth demand for milk and dairy product are expected to grow by 22% between 2012 and 2022 (O'Mara 2012). Grasslands are important to the global food supply as they contribute milk, meat production and a large genetic library for crop (Sala and Paruelo 1997; O'Mara 2012). In 2009 29% of the global meat supply came from cattle

buffalo, sheep and goats, all of which use grasslands as a major component of their diets (O'Mara 2012).

North American Grasslands

North American grasslands (also called the Great Plains) evolved under the rain shadow of the Rocky Mountains. They are characterized by seasonal precipitation occurring mostly in the spring and summer. From the Rocky Mountains east to the Mississippi River precipitation increases and prairie types transition from short-grass prairie to mixed-grass prairie to tall-grass prairie (White, Rohweder, and Murray 2000; Pieper 2005). Historically (pre-European colonization) grasslands dominated central North America extending from central Canada (Alberta, Saskatchewan and Manitoba) south to Texas and from east of the Rocky Mountains in Montana all the way to Illinois and Ohio during warm interglacial periods, covering approximately 162 million ha (Samson and Knopf 1994; White, Rohweder, and Murray 2000). Soils developed from a variety of parent materials including lime-stone, sandstone, shale, metamorphic and igneous outwash and loess. In the southern extent of the Great Plains (between 30° and 42° N) C₄ species dominate while north of 42°N C₃ species become more prevalent (Pieper 2005). Physiologically, C₃ and C₄ plants differ in the photosynthetic pathway by which carbon is fixed into carbohydrate. C₃ species typically have lower light saturation, lower rates of photosynthesis, and higher transpiration rates than C₄ species. Due to these physiological differences, C₃ and C₄ plants respond differently to environmental conditions, and growth varies by season. Plants which utilize the C₃ pathway reach peak growth earlier in the growing season as they are more active in the cooler spring and early fall temperatures. In contrast, C₄ species reach maximum growth later in the growing season as

they are more active under warmer and drier conditions of middle to late summer. Additionally, in tallgrass prairies C₃ species are usually non-native and C₄ species are usually native (Goodin and Henebry 1996).

Short-grass prairie is dominated by blue grama (*Boutelou gracilis*) and buffalo grass (*Bouteloua dactyloides*) and is the least decimated of the three prairie types in North America. However, extensive areas of short-grass prairie have been invaded with invasive perennial and annual species which is primarily attributed to overgrazing by livestock and farming. Mixed-grass prairie is characterized by warm-season grasses in the west and cool season grasses to in the east. As a result of its location on an ecotone mix-grass prairies have higher diversity than the other prairie types (White, Rohweder, and Murray 2000). Tallgrass prairies, which will be the focus of the remainder of this study, are the most decimated of the three with declines since 1830 estimated to be between 82.6% and 99.9% for all states and provinces, which is greater than any other ecosystem found in North America (Samson and Knopf 1994).

Tallgrass prairies are temperate, mesic grasslands primarily consisting of sod forming bunchgrasses and are the most productive of the three grasslands found in North America. Precipitation ranges from 60 cm in the northwest to 100 cm in the southeast and the climate is continental with temperature ranging from -35°C to 45°C. Vegetative composition typically consists of widely distributed core species of warm-season grasses, and secondary less abundant and less dominant grasses and forbs (Knapp and Seastedt 1998). Dominant C₄ grasses include big bluestem (*Andropogon gerardi*), switchgrass (*Panicum virgatum*), and indian grass (*Sorghastrum nutans*). C₃ graminoids are also present in tallgrass prairies with species including Scribners panicum (*Panicum oligosanthos*), porcupine grass (*Stipa spartea*), junegrass (*Koeleria*

macrantha), Kentucky bluegrass (*Poa pratensis*) and a variety of sedge species. While production comes largely from graminoids, forbs contribute the most to richness and diversity and are also more responsive to disturbances such as fire and grazing (Flores 1996).

Fire Disturbance

Primary disturbances in tallgrass prairie include fire, grazing and climate and they are integral factors in determining the shape and structure of plant life history, population dynamics, species interactions and community structure. Plant community structure and composition in turn influence populations of birds, mammals and invertebrates.

Historical fire frequency in tall grass prairie ranged from two to five years, but there was probably large year to year variation (Collins and Steinauer 1998; Steinauer and Collins 1996). Lightning ignited fires occurred from March through December, but were most common in mid-to late summer (Bragg 1982). Additionally, Native Americans ignited fires to attract herbivores and protect their camps (Steinauer and Collins 1996). Perhaps the most apparent effect of fire is the reduction of woody species associated with it. In general, woody plant species decrease with annual spring burning and increase with longer fire-return intervals. In the absence of fire detritus accumulates, woody plants establish, and altered competition leads to an increase in shrub cover and succession to woody-dominated communities (Briggs and Gibson 1992; Briggs, Nellis, and Turner 1998).

Grass and forb response to fire are influenced by their morphologies and phenology's. In the dominant C₄ grasses big bluestem and indian grass, fire stimulates rhizome development in the

early season leading to higher tiller densities and increased establishment. Most cool-season C₃ grasses show decreased flowering and tillering in response to frequent spring fires (Collins and Steinauer 1998). Species that begin growing early in the growing season are killed or damaged by fire so they are then unable to set seeds (Gibson 1988). Most forb species, for example, increase in abundance with decreasing fire frequency. Forbs that flower in the mid- to late summer have reduced growth and vegetative production in response to fire (Hartnett 1990), but this is likely an indirect effect due to increased competition from warm-season grasses (Hartnett 1991). The increase in abundance of most forbs as the fire return interval increases is due to competitive release from warm-season grasses, and therefore, fires reduce overall species richness by selecting for the dominant warm-season grasses (Collins 1992; Collins and Calabrese 2012).

Many tallgrass prairies are managed using spring burns because the forage production of the C₄ grasses are favorable for livestock. Spring burning can increase species richness by opening space for seedling establishment, but summer fires reduce the abundance of C₄ grasses and increase the abundance of C₃ grasses (Howe 1994). Since C₃ grasses have little biomass but there are a large number of species, summer burns can increase diversity but decrease overall productivity. Diversity is maximized several years post-fire, but eventually litter accumulation reduces the competitiveness of C₄ grasses and diversity declines if the prairie is not re-burned (Gibson and Hulbert 1987). When the prairie goes unburned the accumulated litter reduces light levels which suppresses plant growth (Weaver and Rowland 1952), while high light availability and temperatures occur following fire which increases plant production (Knapp 1984).

Grazing Disturbance

Grazing is another primary disturbance which moderates structure and composition in tallgrass prairies. Primary herbivores inhabiting tallgrass prairies before European settlement included bison, elk, white-tailed deer, mule deer, and numerous smaller vertebrate and invertebrates (Collins and Steinauer 1998). While precise knowledge of bison's role in tallgrass prairie is lacking since the extent of the prairie has decreased so rapidly and in concordance with the decline of bison, it has been hypothesized that they played a keystone role in these ecosystems as they alter the competitive balance between many C₄ and C₃ plant species and therefore vegetative composition and structure (Knapp et al. 1999). Bison feed mostly on graminoids (Streuter et al. 1995) while avoiding forbs and woody species which usually contribute to less than 10% of their diets (Damhoureyeh and Hartnett 1997).

It is the forb component that accounts for the highest levels of biotic diversity in tallgrass prairies. Grazing on grasses releases forbs from competition with warm-season grasses thereby increasing levels of biodiversity (Collins 1998; E Gene Towne et al. 2005; Collins and Calabrese 2012). Effects of bison grazing on big bluestem grass differ short term versus long term. Short term, growth enhancement occurs due to increased light availability and reduced water stress (Fahnestock and Knapp 1993). Long term however, the ability of tillers to compensate for the effects of grazing is reduced, and this is likely due to differences in the short and long-term stores in below ground carbon and carbohydrates (Vinton et al. 1993).

While Bison were historically the primary herbivores on tallgrass prairies, they have largely been replaced by cattle, and there are differences in how the two influence prairie dynamics. A large difference between the two, is how they are managed. Cattle grazing usually occurs during the

May-September growing season (E Gene Towne et al. 2005). Bison, however, traditionally remain on pastures year-round with no management. Another difference is that bison body masses for all ages and sexes are lower than those in cattle, and consequently intake and grazing intensity differ (E. G. Towne 1999). A behavioral difference between bison and cattle is that bison create wallows which are depressions in the ground as they paw and roll in exposed soil. These depressions can reach 3-5 m in diameter and 10-30 cm in depth, and vegetation is usually absent (England 1959). Wallows alter patch structure as the depressions can revegetate or remain bare depending on recurrent use by bison and they retain rainwater in the spring which supports ephemeral wetland species and in the summer provide habitat to plants that are tolerant to drought (Polley and Collins 1984). Overall, grazed prairie that consists of bison wallows have higher diversity than without (Collins and Barber 1986).

There are also differences in how bison and cattle grazing affect species composition. It has been found that big bluestem cover increases under cattle grazing, but not bison. Conversely, little bluestem cover can decline under bison grazing, but not cattle. While forbs increase under both bison and cattle grazing, the increase is largest with bison. Additionally, species diversity and richness is highest under bison pastures, although only slightly higher than with cattle (Hartnett, Hickman, and Walter 1996; E Gene Towne et al. 2005). Regardless, both bison and cattle grazing have a large impact on tallgrass prairie composition and structure.

Climate Disturbance

A third major disturbance which influences tallgrass prairie structure is climate. Perhaps the largest influence of climate on tallgrass prairies is on aboveground net primary productivity (ANPP). Solar radiation and temperature have been found to be correlated with ANPP, but it is precipitation

that is the most influential (Sala et al. 1988). Both annual and seasonal precipitation have been found to be positively correlated with ANPP which highlights the importance of water as a limiting resource. At low fire frequencies, reductions in light availability probably outweighs moisture availability and water only limits production in extremely dry years, or dry locations (such as uplands). Additionally, just as fire and grazing influence relative abundance of C₃ and C₄ plants, so does climate. C₃ plants achieve peak growth earlier in the growing season and are most active in the cooler spring and early fall temperatures. C₄ species reach maximum growth later in the growing season and are most active in the middle to late summer. As such, fluctuations in annual and seasonal temperature and precipitation are likely to shift the relative abundance of C₃ and C₄ plants as C₄ plants might begin expanding farther north due to increased temperatures.

It has also been hypothesized that increasing atmospheric CO₂ will result in increased coverage of C₃ plants (due to increased photosynthetic rates) at the expense of the dominant C₄ plants which would reduce the overall productivity of tallgrass prairies, but research on the Konza Prairie has shown that in order to understand the effects of increasing CO₂ on tallgrass prairie communities it is necessary to understand the interaction between CO₂ and plant water relations. By comparing ambient CO₂ levels to twice ambient levels over an eight year period Knapp et al. (1996) found that increased CO₂ led to improved water use efficiency due to reduced stomatal conductance for the dominant C₄ grass big bluestem in both wet and dry years. This suggests that in dry years increased water use efficiency of C₄ plants may buffer the effects of increased photosynthetic rates in C₃ plants. This is confirmed by Knapp et al. (1993) where at elevated CO₂ levels in years where plants were not limited by precipitation and that big bluestem did not experience any enhancement in photosynthetic rates compared to ambient CO₂ levels. In contrast, in dry years plants exposed

to ambient CO₂ levels had lower photosynthetic rates than those exposed to elevated levels, likely due to the increased water use efficiency at elevated CO₂. Therefore, annual and seasonal precipitation may also moderate the influence of CO₂ when determining abundance of C₃ and C₄ plants.

The Konza prairie will be referenced throughout this research as it a Long-Term Ecological Research (LTER) center located on a tallgrass prairie in Kansas which was established in 1980. This location offers an abundance of research which has examined how disturbances (among other topics) influence tallgrass prairie dynamics, and it is likely that processes operating at this location are also important on the SNG.

Growing season temperatures have been found to be the most influential variable controlling C₃ and C₄ compositions while summertime precipitation explains less, but still significant variance (Teeri and Stowe 1976). In general, increases in wintertime precipitation and lower annual temperatures increase abundance of C₃ grasses while increases in mean annual temperature and increases in summertime precipitation increase abundance of C₄ grasses. Additional studies have also found fire, grazing, soil properties and topography to be influential drivers in relative C₃ and C₄ abundance, although these factors are of secondary importance to climate (Paruelo et al. 1997).

Physiologically, C₃ and C₄ plants differ in the photosynthetic pathway by which carbon is fixed into carbohydrate. C₃ species typically have lower light saturation, lower rates of photosynthesis, and higher transpiration rates than C₄ species. Due to these physiological differences, C₃ and C₄ plants respond differently to environmental conditions, and growth varies by season. Plants which utilize the C₃ pathway reach peak growth earlier in the growing season as they are more active in the cooler spring and early fall temperatures. In contrast, C₄ species reach maximum growth later

in the growing season as they are more active under warmer and drier conditions of middle to late summer. Additionally, in tallgrass prairies C₃ species are usually non-native and C₄ species are usually native (Goodin and Henebry 1996).

State and Transition Models

Understanding how tallgrass prairies respond to disturbances such as fire, grazing and climate, and predicting how future management and climate regimes may cause transitions in species compositions is critical to make appropriate management decisions and to evaluate how these transitions influence ecosystem functions. For instance, numerous catastrophic ecosystem transitions have been documented in arid and semi-arid regions of the world, and these transitions often involve the loss of perennial grasses and their replacement by trees/shrubs. Transitions are accompanied by loss of soil fertility, plant community variability, biodiversity, and livestock production. Often times these transitions are irreversible and simply reducing the cause of the change, will not revert the ecosystem back. Because of this, public and private resource managers are interested in predicting, halting and reversing vegetative state changes and transitions (Bestelmeyer et al. 2006).

State and transition models (STM's) have been developed which describe a set of discrete "states" of vegetation and a complementary set of discrete "transitions" that can occur between the states (Westoby, Walker, and Noy-Meir 1989; Briske, Fuhlendorf, and Smeins 2003; Stringham, Krueger, and Shaver 2003). A state is a persistent vegetative community, and "transitions" are trajectories between the states that are often the result of disturbances such as climate, fire or grazing. Transitions can occur quickly, such as when a large fire occurs, or they can be slow and gradual such as when there is a subtle shift in climate (Westoby, Walker, and Noy-Meir 1989;

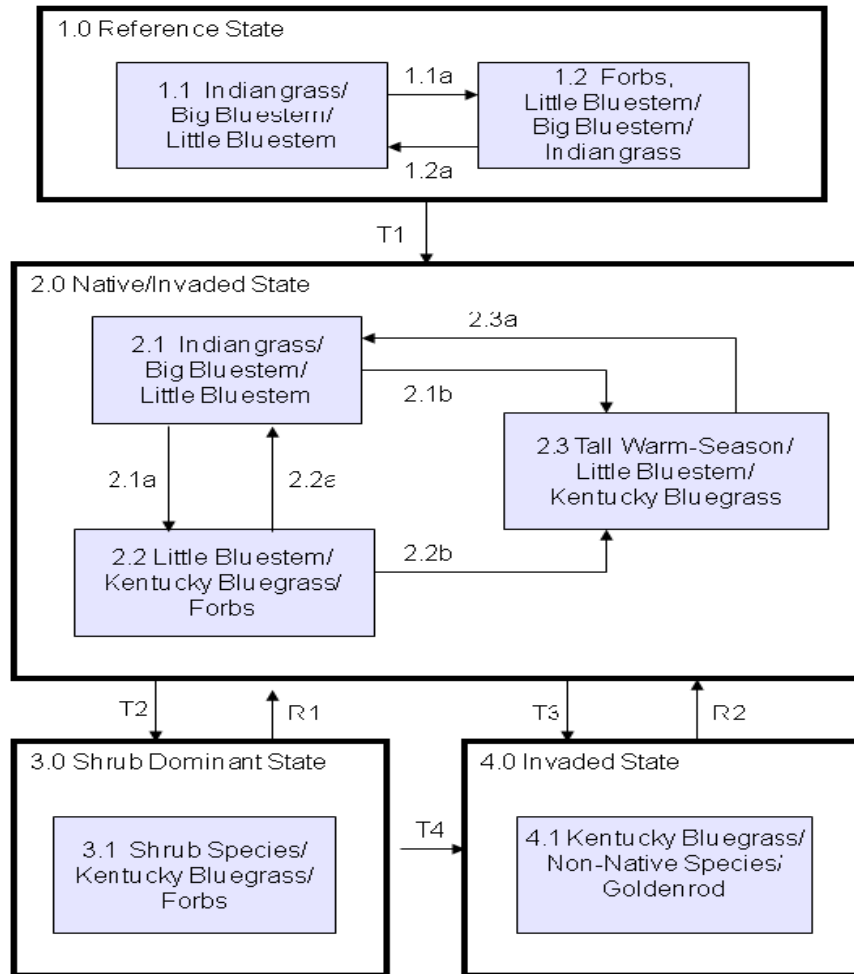
Stringham, Krueger, and Shaver 2003). In this way there can be multiple alternative stable states and multiple transitions that can cause an ecosystem to reach a particular state.

In order for state changes to occur in a STM a threshold must be reached which causes the change. This does not mean that species composition within states are static, rather, there is a potential for large variation even within states, but when a state change occurs the primary ecological processes are changed and a different potential set of plant communities results. The basis of rangeland and prairie ecosystems is the soils which have developed from specific parent materials, climate, and the interaction of soil and terrestrial organisms. These factors provide the basis for establishing a site's ecological states (Stringham, Krueger, and Shaver 2003).

The USDA Natural Resources Conservation Service (NRCS) has implemented the use of STM's for rangeland ecological sites across public lands in the United States, and they are termed Ecological Site Descriptions (ESD). ESD's are based upon soil types, and more accurately soil complexes. As an example, the state-and-transition model for the Limy Subirrigated site in the Red River Valley of North Dakota is shown in Figure 1. Soils in the Limy Subirrigated ESD include loamy fine sands and silty clays which are very deep, relatively poorly drained and have a calcareous subsoil. There are four main states for this ESD, consisting of reference, native/invaded, shrub dominant and invaded state. The reference state represents the natural range of variability that dominated this ESD without human intervention, Native/Invaded is similar to reference in appearance and function but has a higher proportion of invasive or introduced species, the shrub dominant state is characterized by dominance of shrubs and a understory of cool-season sod forming grasses and the invaded state is complete dominance of introduced species, primarily Kentucky bluegrass (*Poa pratensis*) in this case. Once the invaded state is established even

largescale events such as high intensity fire cannot reduce Kentucky bluegrass. The variety of pathways that are hypothesized to lead to transitions between states are also highlighted within the figure.

The description provided above represents just one state-and-transition model provided by the NRCS ESD's, and each site which is based on different soil types has variation in the states and transitions that are present and the disturbances which trigger them. By identifying which state prairies and rangelands are currently in land managers are better able to identify the health of the system they are trying to manage, and what the management options are that may transition the ecosystem into a desired state. The drawback to this is that extensive field work is often required to collect information on species composition and the extent of invasion by non-natives which is expensive. Because of these limitations in field sampling, remote sensing has the potential to be a powerful tool in assessing changes through time in grassland communities, and possibly to even differentiate between different grassland states and transitions (Hunt, Jr. et al. 2003; Hill 2013; Hill et al. 2013). These changes may relate to the transitions detailed in the ESD's. Satellite sensors are also well suited to evaluate ecosystem change because they provide consistent and repeated observations over a spatial scale large enough to capture the effects of both natural and anthropogenic disturbances (Kennedy, Cohen, and Schroeder 2007; J. E. Vogelmann, Tolk, and Zhu 2009).



1.1a – Reduced precipitation, increased disturbance; **1.2a** – Return to normal precipitation and disturbance; **T1** – altered disturbance regime and introduction of non-native species; **2.1a** – heavy grazing without adequate recovery periods; **2.2a, 2.3a** – Prescribed grazing and prescribed fire; **2.1b, 2.2b** – removal of fire and grazing; **T2** – No fire; **T3** – cropped go-back, heavy grazing or extended periods of non-disturbance; **T4** – Brush control, prescribed fire; **R1** – Brush control, range seeding, prescribed fire and prescribed grazing; **R2** – Range seeding, prescribed fire, prescribed grazing

Figure 1. State and Transition Model for the Limy Subirrigated Site in the Red River Valley of North Dakota.

Remote Sensing Applications

Remote sensing of grasslands is difficult because grasslands are heterogeneous and patchy, especially at the moderate spatial resolutions offered by most satellites (Hill 2013). Thus far most of the research using satellite remote sensing has proven most effective at examining temporal and regional trends in phenology and productivity rather than in discrete within state changes.

Likely the most commonly used vegetative index to characterize biophysical parameters is the normalized difference vegetative index (NDVI) (Running, Loveland, and Pierce 1994) which is computed as the difference in reflected energy at the near-infrared (NIR) and red wavelengths which can be used to measure the photosynthetically active biomass in plants (Tucker 1979). The NIR constitutes wavelengths between 700-1100 nm and the red is between 600-690 nm. NDVI has been found to be correlated to leaf area index (LAI), biomass, percent vegetation cover, and canopy nitrogen and chlorophyll content (Gamon et al. 1993).

Many studies have also examined how phenology has varied through time using NDVI (Zhang et al. 2003). Monitoring of phenology is characterized by four key characteristics: (1) greenup, which marks the beginning of photosynthetic activity; (2) plant maturity which is when maximum plant leaf area is reached; (3) senescence which marks a sharp reduction in photosynthetic activity; (4) and dormancy which is when photosynthetic activity is near zero. By analyzing time series composites of AVHRR or moderate resolution imaging spectroradiometer (MODIS), changes in phenology over time can be evaluated in relation to factors such as climate and human intervention.

Applications of Vegetation Indices

While parameters such as biomass and phenology do provide important insights into ecosystem status and function, by themselves they are not capable of predicting the subtle within state changes which are so important for grassland management. A major challenge in remote sensing thus far is that satellite imagery is not capable of determining individual species, even when small pixel sizes are used (high resolution imagery) (Hunt, Jr. et al. 2003). However, the reflectance spectrum from remote sensing can provide information about chlorophyll content, water content and leaf and canopy structure which can provide insights into the functional characteristics of ecosystems (Gates et al. 1960; Knipling 1970).

Suites of vegetative indices (VI) have the potential to be useful indicators of rangeland status, but little research has examined the capability so far (Hill 2013; Hill et al. 2013). Hill (2013) evaluated a suite of VI's across a range of prairies including xeric mixed, mesic mixed, mixed grass, saline tallgrass, tall grass prairie/oak savanna and Post oak savanna. Additionally, VI's were evaluated across different land cover classes, and vegetative states which were essentially simplified versions of the ESD's did show that VI's can be useful indicators of vegetative states in grasslands as savannas. Vegetative indices used included the NDVI which is used as an indicator of photosynthetic pigment and biomass; the Carotenoid Reflectance Index I (CRI1) which is sensitive to yellow pigments; the Anthocyanin reflectance Index I (ARI1) which is sensitive to red pigments and stress; the Red Green Ratio (RGR) which is sensitive to red pigments and stress as well (but less sensitive than ARI1); the Normalized Difference Infrared Index (NDII) which is sensitive to vegetative moisture and correlated to biomass; the Soil Adjusted Total Vegetation Index (SATVI) which is sensitive to grassland biomass under senescent conditions; and the Short Wave Infrared

Ratio (SWIR32) which is sensitive to non-photosynthetic vegetation. Of these VI's, the NDVI, NDII, RGR and SWIR32 are readily calculated from multispectral sensors such as Landsat. While this study only examined VI's over a single date image, multi-date analysis could offer improvements as phenological and spatial variation would be better captured and could help characterize changes in grassland ecosystems.

Many studies have employed remote sensing to detect and map change, but often times these studies focus on abrupt changes such as logging, agriculture expansion, or fires which are much easier to detect than the subtle within-state changes which often occur in grasslands (Coppin et al. 2004; Hansen et al. 2008). Within-state changes often happen very gradually, but nevertheless still have important impacts of ecosystem processes which influence the carbon balance, biochemical cycles and patterns of biodiversity (Perry and Millington 2008). Further obstacles which have made detection of subtle ecosystem change difficult is the necessity to have access to calibrated multi-temporal imagery and access to adequate field data, but despite these limitations there have been a number of successful studies which have utilized remote sensing to detect and monitor gradual state changes within ecosystems (Beck et al. 2007; Röder et al. 2008; J. E. Vogelmann, Tolk, and Zhu 2009).

Detecting Ecosystem Changes with Regression

Initially many change detection studies focused on simply subtracting two images from each other over a specified time frame to evaluate changes in spectra, but this method prevents evaluation of long term trends and is more appropriate for abrupt change than subtle change (Coppin et al. 2004). More recently trend analysis through regression has proven to be particularly useful for evaluating both abrupt and subtle changes in forests, particularly when using long term datasets such as those

provided by the Landsat sensors. Trend analysis is based on the premise that if a change in an ecosystem has occurred there will be a distinct shift in the spectral signature over a specified time period. In contrast to two date image differencing, trend analysis allows for evaluation of change over much broader temporal trajectories. Simple linear regression has been employed to assess change because if a specific pixel is shown to fit a particular change trajectory it is likely that that pixel has experienced the trajectory described. Assessing change with linear regression provides insight into locations of change, the magnitude of change, which vegetation communities have been most impacted, and potentially what the cause of the change is itself. An inherent difficulty of time series analysis is the lack of ancillary data needed to validate findings which is often needed on an almost yearly temporal scale (Kennedy, Cohen, and Schroeder 2007; Röder et al. 2008; J. E. Vogelmann, Tolk, and Zhu 2009).

Vogelmann et al. (2009) evaluated per pixel trajectories of forested ecosystems in New Mexico with 10 Landsat images acquired between 1988 and 2006 to determine if dieback of forest had occurred due to insect damage. Analysis focused solely on the Shortwave Infrared/Near Infrared (SWIR/NIR) index and the NDVI, both acquired from Landsat. To map change linear regression was used whereby VI value per pixel was used as the dependent variable and time was used as the independent variable. Images which differentiated pixels with significant change at p-values of 0.01 and 0.05 levels of confidence were then mapped in conjunction with whether slopes were increasing or decreasing per pixel. To assist in interpreting how regression models varied by forest type a classified image from the LANDFIRE project (<https://www.landfire.gov/>) was used to assign membership of forest type (e.g. Spruce–Fir, Mixed Conifer, deciduous forest) to each pixel. Based on this analysis it was found that the spruce/fir forests had many more pixels which showed

a statistically significant trend compared to deciduous and mixed conifer forests, and thus were likely most influenced by dieback.

Building on this study, Vogelmann et al. (2012) conducted a study which implemented linear regression per pixel with NDVI and SWIR/NIR across four separate ecosystems in four different regions of the U.S.: (1) forest and rangelands in the southwestern U.S.; (2) sagebrush rangelands in Wyoming; (3) woodland/prairie in Nebraska; and (4) forests in New Hampshire. Overall it was found that conifer forests in the southwest were experiencing decreasing NDVI (increasing SWIR/NIR) due to insects and drought; sagebrush communities were decreasing in NDVI and increasing in SWIR/NIR due to fire, mining and drought; forest communities in Nebraska were expanding into the prairie and increasing in NDVI and forests at high elevation in New Hampshire were increasing in NDVI likely due to understory species moving to higher elevations with time.

The studies described above have only used regression to evaluate change by using time as the dependent variable and in forested ecosystems, but it may also be useful to evaluate how climate and management influence VI response and in ecosystems other than forests. Roder et al. (2008) examined the effect of grazing in Mediterranean grasslands in Greece by implementing regression per pixel after applying spectral mixture analysis (SMA), which estimates fractional cover of vegetation, soil, and shade. In this way grazing pressure was used as the independent variable and fractional cover of vegetation the dependent variable, but results were highly variable with some plant communities having decreased vegetative cover with increased stocking rate, some having increased cover and some having no relation at all.

Simple linear regression has been shown to be an effective tool to characterize subtle change trajectories of individual pixels through time, but most research using this methodology has been

limited to forested ecosystems, and has only focused on evaluating change in VI values through time, not in relation to climate variables or management decisions. The remainder of this study will focus on implementing the regression based change detections previously described on the SNG. Additionally, a variety of VI's will be evaluated including the NDVI, NDII, RGR and SWIR32 and multiple independent variables will be evaluated including time, precipitation, growing degree days and grazing pressure to determine how each influence VI values. Lastly, multiple regression will be used to determine how multiple independent variables at once influence overall model fits and random forest regressions will be used to evaluate feature importance of VI values.

CHAPTER III

METHODS

Study Area

The Sheyenne National Grassland (SNG) is managed by the U.S. Forest Service within the U.S. Department of Agriculture (USDA) and is located in southeastern North Dakota. Average precipitation is 530 mm per year (USDA Forest Service 2001). At 28,000 ha, the SNG represents the largest publicly owned tract of eastern deciduous forest, oak savannah and northern tallgrass prairie in the state. The tallgrass prairie and oak savannah ecosystems represent the largest publicly owned tracts remaining in all of North America. The tallgrass prairie is one of the rarest ecosystems left on Earth, and the bur oak savannah is considered a regionally threatened ecosystem. As such, the grassland has high conservation value and is home to numerous sensitive species, and one endangered species. The grassland is far from pristine though, and suffers problems including invasive forb and grass invasion, expansion of trees and shrubs, and overgrazing (Svingen, Braun, and Gonzalez 2008).

To fully understand the SNG's vegetative composition, it is important to first review the areas geologic past which was of critical importance in soil formation. 10,000 to 15,000 years ago southeastern North Dakota was covered by glacial ice which deposited crushed rock (called glacial till) across the landscape. Around 13,000 years ago the climate warmed, and the glaciers began to recede. As the ice melted rivers began transporting large volumes of meltwater, but the Red River

was blocked by glacial ice farther north which had not melted. This water then began accumulating forming what is known as glacial Lake Agassiz, which at one point covered approximately 900,000 square km across portions of North Dakota, Minnesota, Manitoba, Saskatchewan and Ontario (Fritz 2001). Streams such as the Sheyenne River (which flows through the SNG) deposited sediments with their meltwater into Lake Agassiz. The area where these sediments were deposited is known as the Sheyenne Delta. Since fine sediments such as silt and clay are lighter, they were transported further into Lake Agassiz than were coarse sediments such as sand and gravel. As such, sand and gravel was deposited at the Sheyenne Delta while the clay and silt particles were deposited onto the lake floor. The area where the clay and silt particles were deposited is now known as the Red River Valley and represents extremely fertile land which is productive for agriculture.

As the climate continued to warm and the glaciers melted, Lake Agassiz disappeared and the Sheyenne Delta become exposed to wind which worked the sediments into eolian landforms which are present on the SNG today. These landforms (Figure 2) include the deltaic plains (DP), sand dunes (SD) and hummock and swale (HS). Additionally, the Sheyenne River continued to drain central North Dakota, and through time it meandered back and forth carving out the last landform, which is the Sheyenne river bottom (Svingen, Braun, and Gonzalez 2008).

The choppy sand hills landform consists of ridges of sand that reach up to nine meters high and has vegetation which prefers dry sandy soils such as bur oak (*Quercus macrocarpa*) smooth sumac (*Rhus glabra*), sand bluestem (*Andropogon hallii*), and needle and thread grass (*Stipa comata*). This landform is primarily found within 5 km of the Sheyenne River.

The hummock and swale landform has parabolic dunes (hummocks) which also typically have a depression (swale) on the upwind side which support wetland plants. Vegetation includes blue grama (*Bouteloua gracilis*), switchgrass (*Panicum virgatum*), and sedges (*Carex spp.*) on the hummocks, and northern reed canary grass (*Calamogrostis stricta*), sloughgrass (*Beckmannia syzigachne*), and Baltic rush (*Juncus balticus*) in the swales.

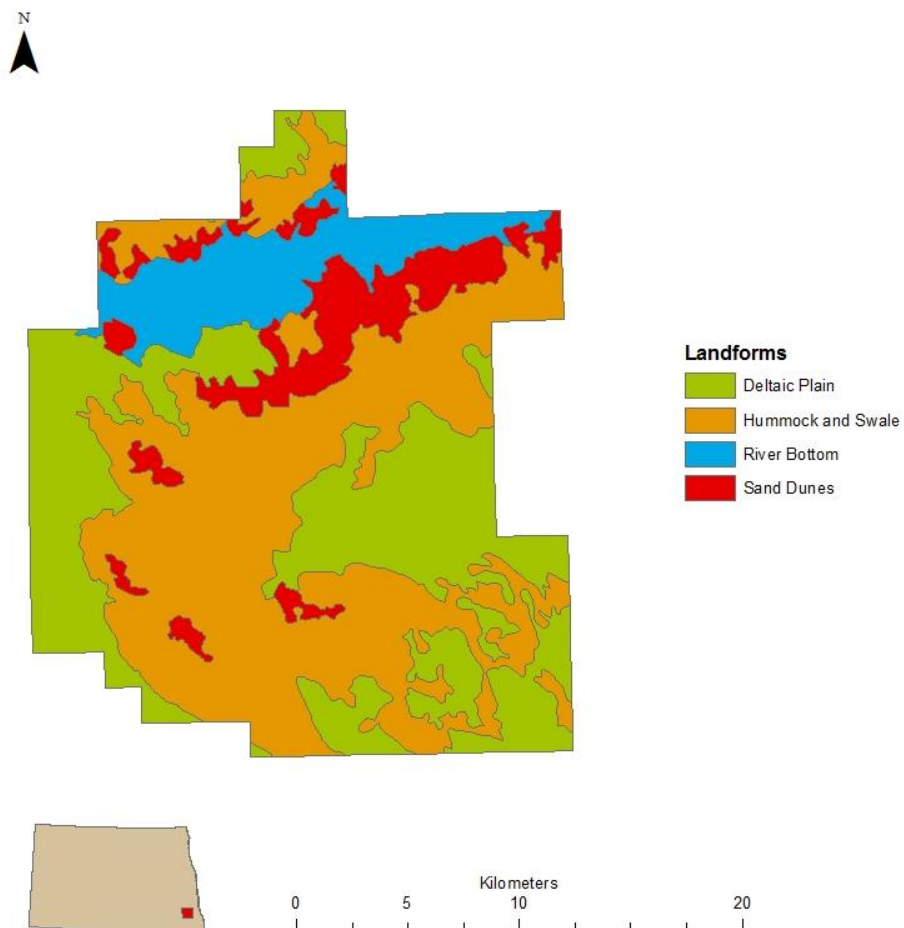


Figure 2. Location and landforms of the SNG.

The deltaic plains landform is relatively flat and has sandy soils which can reach up to 3 meters thick. Well drained areas support tallgrass prairie and depressions support sedges. Typical vegetation includes big bluestem (*Andropogon gerardii*), and Indiangrass (*Sorghastrum nutans*).

The Sheyenne River valley landform is shaped by the meandering of the Sheyenne River and includes flat flood plains, wetlands and sloping terraces. On the terraces eastern hardwood forest, woodland and wetland plants can be found with many of the plants being rare in North Dakota. Vegetation includes American elm (*Ulmus americana*), basswood (*Tilia Americana*), green ash (*Fraxinus pennsylvanica*), boxelder (*Acer negundo*), and hackberry (*Celtis occidentalis*) (Svingen, Braun, and Gonzalez 2008). The River Bottom landform occupies only a small area of the SNG and therefore will not be further discussed in this analysis.

In addition to the landforms, there are many hundreds of plant species occurring in a number of major species associations on the SNG, but only limited data are available describing the geographical patterns of botanical composition and individual dominant species gradients. The most detailed and accurate survey to date comes from a USDA National Gap Analysis Program (GAP) (<https://gapanalysis.usgs.gov/data/>) survey completed between 1992 and 1999 (Figure 3). The GAP was created by integrating spectral response from Landsat 5 images with training data acquired from ground plots. Training data for tallgrass prairie ecosystems was provided by the North Dakota National Heritage Program (NDNHP). NDNHP completed surveys in Ransom and Richland County, which is where the SNG is located, and some inventory locations were on the SNG itself. Additionally, the NDNHP surveys classified vegetation at the National Vegetation Classification Standard (NVCS) level 8, which is the most detailed level of classification in the

program. As such, GAP classes used in this study were not derived by the author, but are instead based on the NVCS classification system.

GAP grassland communities found on the SNG include bluestem-needlestem-wheatgrass (BNW), planted herbaceous perennials (PHP), wheatgrass prairie (WGP), wet-mesic tallgrass prairie (WMTGP), mesic tallgrass prairie (MTGP), sand prairie (SP) and wetlands. WGP and forest/shrubland have very low spatial cover, and therefore will not be used as a basis for evaluation when comparing temporal trends and spatial patterns by vegetation community.

BNW represents transitional prairie that is representative of mixed-grass prairies. Common species include *Schizachyrium scoparium*, *Hesperostipa spartea*, *Nassella viridula*, *Andropogon gerardii*, *Panicum virgatum*, *Pascopyrum smithii*, *Elymus trachycaulus*, *stipa comata*, *Bouteloua gracilis*, *Poa prantensis* and *Bromus inermis*. PHP represents planted perennial grasses and forbs and often includes invasive species such as smooth brome (*Bromus inermis*), leafy spurge (*Euphorbia esula*) crested wheat grass (*Agropyron cristatum*) and Kentucky bluegrass (*Poa prantensis*). WMTGP represents vegetation on low lying lands with high water availability. Common species include *Spartina pectina*, *Calamagrostis canadensis*, *Calamagrostis stricta*, *Carex lanuginosa*, *Andropogon gerardii* and *Panicum virgatum*. MTGP is very similar to WMTGP as the soils have high water availability and often receive runoff from adjacent land, but with slightly different indicator species which include *Andropogon gerardii*, *Sorghastrum nutans*, *Panicum virgatum* and *Schizachyrium scoparium*. The WMTGP and MTGP are the most representative classes provided by GAP of what the species composition on a native tallgrass prairie would look like. Lastly, SP represents vegetation on poorly to moderately well-developed soils with low water availability and excessive drainage. Species with deep roots are favored as there is high water availability deeper

in the soil profile than the surface. Common species include *Calamovilfa longifolia*, *Andropogon hallii*, *Hesperostipa comata*, and *Bouteloua gracilis* (Strong, Sklebar, and Kermes 2005).

In relation to ecological site descriptions's, BNW represents native/invaded sites, PHP represents invaded sites, and WMTGP and MTGP represent reference sites. Since the GAP vegetation was created with Landsat 5, it has the same spatial resolution as the images used in this studies analysis. Therefore, it was possible to stratify each pixel on the SNG as a specific GAP community class. The GAP grassland classes described above along with the three landforms are referenced throughout this analysis as they are the primary data sources to evaluate changes in distinct edaphic locations and in species composition.

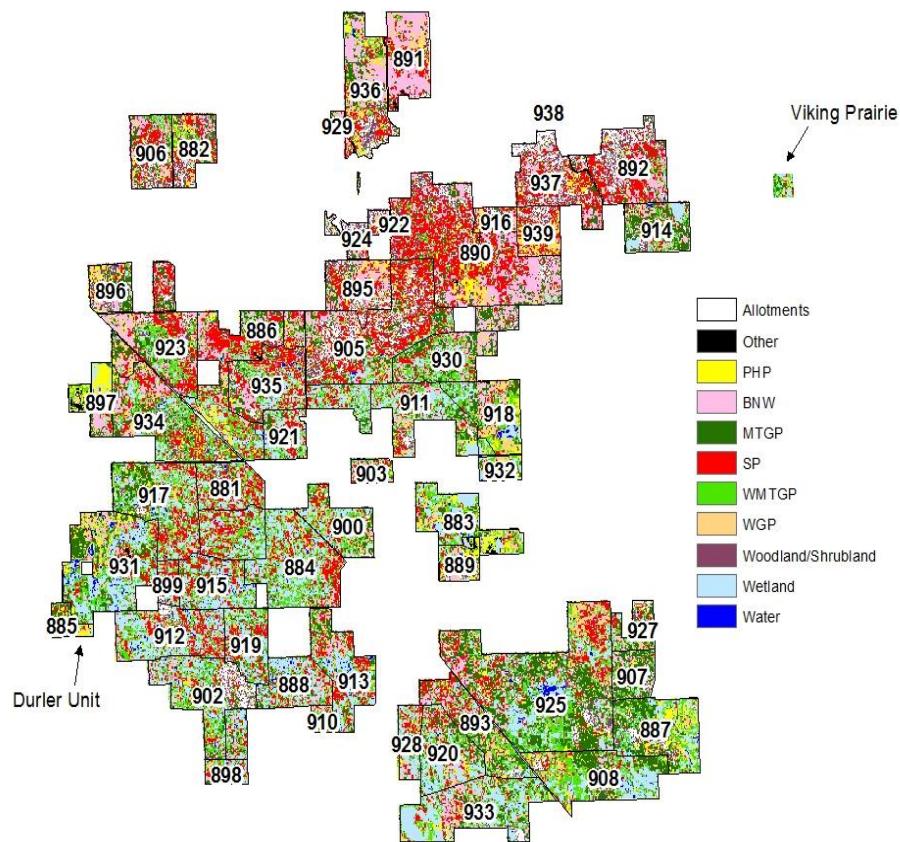


Figure 3. Spatial location of GAP community classes on the SNG and grazing allotments. Numbers identify distinct grazing

Conceptual Framework

Figure 4 provides a flow chart which details the steps taken (aside from image processing) to analyze how conditions have changed on the SNG throughout the time series and what variables will be evaluated as possible drivers of change. Once all the images were downloaded and processed the first step was to evaluate how VI responses differ spatially. Pearson correlation coefficients were used to evaluate resemblance of VI response to one another on a per pixel basis. This is referred to as Stage 1 in Figure 4. It is hypothesized that a pixel with a large NDVI value will also have a large NDII value because higher photosynthesis should be coupled with higher vegetation moisture, and therefore a strong positive correlation. It is also hypothesized that a pixel which has a strong NDVI or NDII value will also have a smaller RGR or SWIR32 value and therefore a strong negative correlation because high photosynthesis and high moisture should be coupled with low stress and low non-photosynthetic material. RGR and SWIR32 should also have a strong positive correlation with each other as more stress should be coupled with more non-photosynthetic material. Lastly, the composite index (CI) (see later methods for calculation of this VI) should have a strong positive correlation with NDVI and NDII and a strong negative correlation with RGR and SWIR32. By examining the relationships in the remotely sensed response on a per pixel basis between VI's it should be possible to identify locations where certain VI's detect unique ecosystem attributes.

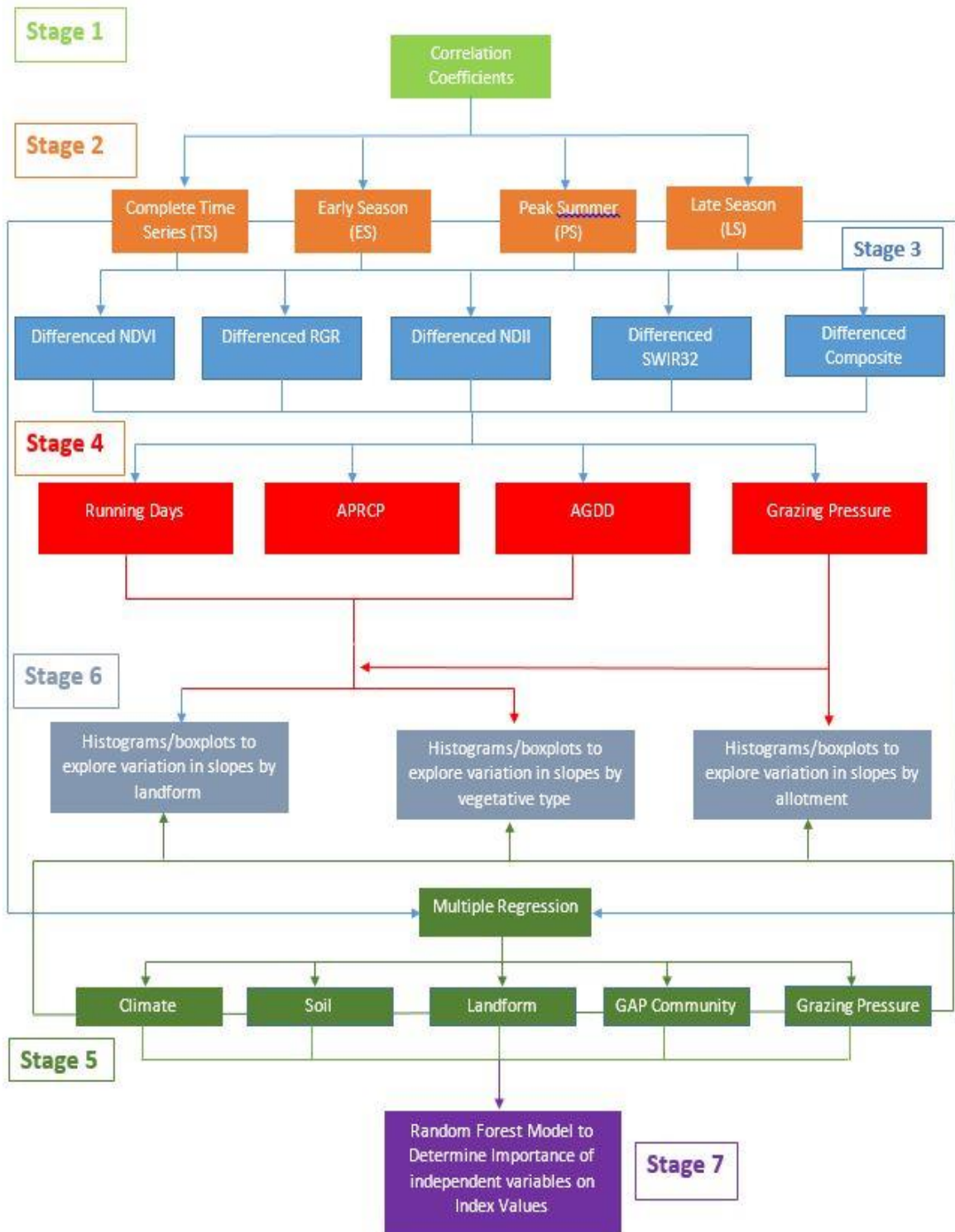


Figure 4. Conceptual Framework.

It was also of interest to determine how correlation coefficients vary between VI's through the entire time series stack as well as different parts of the growing season. This is referred to as Stage 2 in Figure 4. Correlation coefficients were evaluated for all VI's for the following combinations of dates:

1. A 'Complete Time Series' (TS) model whereby all images in the time series are included in the regression.
2. An 'Early Season' (ES) model where only images acquired in May and June are included.
3. A 'Peak Summer' (PS) model where only images acquired between July 1st and August 20th are included
4. A 'Late Season' (LS) model where only images acquired between August 21st and September 30th are included.

For instance, when evaluating coefficients for the Complete Time Series all 79 images were used in analysis. When evaluating the Early Season, only images which were acquired within May and June were included.

Having assessed spatial inconsistencies in VI values by season, the third step was to determine if a change in index response had taken place through the time series. This is referred to as Stage 3 in Figure 4. To determine if change had taken place the time series was split into images acquired between 1984 and 1995 (time period one) and images acquired between 2004 and 2011 (time period two). Equal number of images in each of the two new time periods were then selected, and the mean (per pixel) of the images in each time period were calculated. The date ranges selected in each of these two time periods was selected to ensure that the exact number of images from any

unique month were compared in each time period. Lastly, these images were simply differenced by subtracting time period two by time period one to determine if index values had increased or decreased per pixel.

Once it was determined if pixel values had changed, regression models were implemented to determine the magnitude and significance of change. For four of the independent variables (precipitation, growing degree days, grazing pressure and number of days elapsed in the time series) simple linear regression models were explored for each index, and multiple regression was used to include additional variables such as soil properties, species composition and landforms. Independent variables included in simple linear regression are referred to in Stage 4 in Figure 4 while independent variables included in multiple regression are referred to in Stage 5. Independent variables in Stage 4 are hypothesized to be those most influential on VI values.

To determine if VI values had changed through time, the 'Running Days' regression was used whereby change in VI value per day is estimated. Using time as an independent variable is a mechanism to determine if subtle ecosystem changes have taken place through time itself. These changes may have substantial impacts on ecosystem processes such as carbon storage, biochemical cycling and biodiversity (James E Vogelmann et al. 2012).

Due to the variability in C₃ and C₄ response to climate, antecedent growing degree days (AGDD) and antecedent precipitation (APRCP) were evaluated as independent variables. By evaluating response of each pixel to AGDD and APRCP through different time segments (Stage 2) it may be possible to identify locations which have a larger relative abundance of C₃ or C₄ grasses. Since winter precipitation increased C₃ grass abundance and summer precipitation and temperature increased C₄ abundance at the Konza tallgrass prairie in Kansas (Paruelo and Lauenroth 1996) it

is hypothesized that increases in APRCP in the winter / spring will also lead to increasing abundances of C₃ grasses while increases in AGDD and APRCP in the summer will lead to increasing abundance of C₄ grasses. Accumulations in AGDD and APRCP begin on February 1st for images acquired in May to incorporate winter precipitation (which drives C₃ abundance) while for all other images AGDD and APRCP accumulations begin two months prior to image acquisition. In this way the influence of relatively recent climatic events can be evaluated on VI response.

Grazing is also expected to influence C₃ and C₄ plant communities differently, and to be a driving factor on vegetative condition in general. It has been found that by decreasing the cool season C₃ grasses that nutrient availability increases for warm season C₄ grasses later in the growing season, and increases their biomass (Hartnett, Hickman, and Walter 1996; E Gene Towne et al. 2005). Although cattle selectively graze live and green vegetation, which may decrease the amount of aboveground biomass, this is less important in mesic environments where soil moisture is seldom limiting. In more xeric environments this exposes non-photosynthetic material closer to the ground and should increase SWIR32 in all seasons (Numata et al., 2007).

Since grazing physically interferes with the herbaceous canopy that contributes reflected radiation to the sensor for derivation of vegetation indices, only the individual VIs (not the CI) are used in this analysis to tease out component effects, and to avoid the aggregation of effects represented by the CI. It was hypothesized that increases in grazing pressure resulting from introduction of livestock early in the season will reduce the vigor of any tussocky C₃ grasses but aid in the spread of sod-forming C₃ grasses tolerant of defoliation such as Kentucky bluegrass and deep rooted colonizing weeds such as leafy spurge (termed the Early Season in this study). It was further

hypothesized that maintaining continuous stocking into the Peak Summer season would suppress the growth and vigor of C₄ grasses since the main species have large tillers and crown structures and add biomass by vertical growth. Since C₄ grasses do not commence to grow until frost has completely ended and night temperatures generally exceed 10°C, they do not compete at all in the Early Season. If stocking is maintained into their main summer growth season, their vigor and competitiveness is reduced, and their fractional composition of the sward will decline year by year. In terms of VI responses, an increase in invasive C₃ species would be expected to result in higher NDVI and lower SWIR32 early in the growing season. In addition, these species are favored by higher moisture levels. Areas that are rested and have good stands of native tall grass prairie with C₄ grasses would be expected to exhibit lower Early Season NDVI, and lower NDVI in late summer since the C₄ grasses move rapidly into reproductive growth resulting in tall stands with high levels of cellulose and lignin. Continuous grazing favors short stature, sod-forming and annual grasses that may hay off completely in mid-summer since they do not grow well at high temperatures. However, this behavior may be moderated by presence of sub-soil moisture throughout the growing season.

Regressions were executed on a per pixel basis so that variation in R², slopes and p-values could be compared spatially. Boxplots of slopes and R² for significant pixels were also stratified by landform and GAP to evaluate differences in regression results. Box plots of slopes are only shown for significant pixels ($\alpha \leq 0.05$) from the regression results. Box plots allow for easy comparison of median and interquartile ranges among landforms and vegetation types. Exploration of slopes and R² values with boxplots is referred to in Stage 6.

To compare results found from simple regression and multiple regression, a random forest regression model was used to evaluate feature importance among independent variables. Feature importance was evaluated for all VI's and across the same four time periods shown in Stage 2. Random forest regressions are referred to in Stage 7.

Image Processing

Landsat TM 5 data were downloaded for all cloud free, or nearly cloud free dates ranging from 1984-2011 and for the months of May, June, July, August, and September. This resulted in 79 images available for study. Figure 5 shows a scatter plot of Landsat scenes by image date which were used in this analysis. Images were downloaded from the U.S. Geological Survey (USGS) earth explorer (<http://earthexplorer.usgs.gov/>), and constitute atmospherically corrected surface reflectance. Any remaining clouds in the images were masked out with the provided cloud mask using ESRI's ArcGIS™.

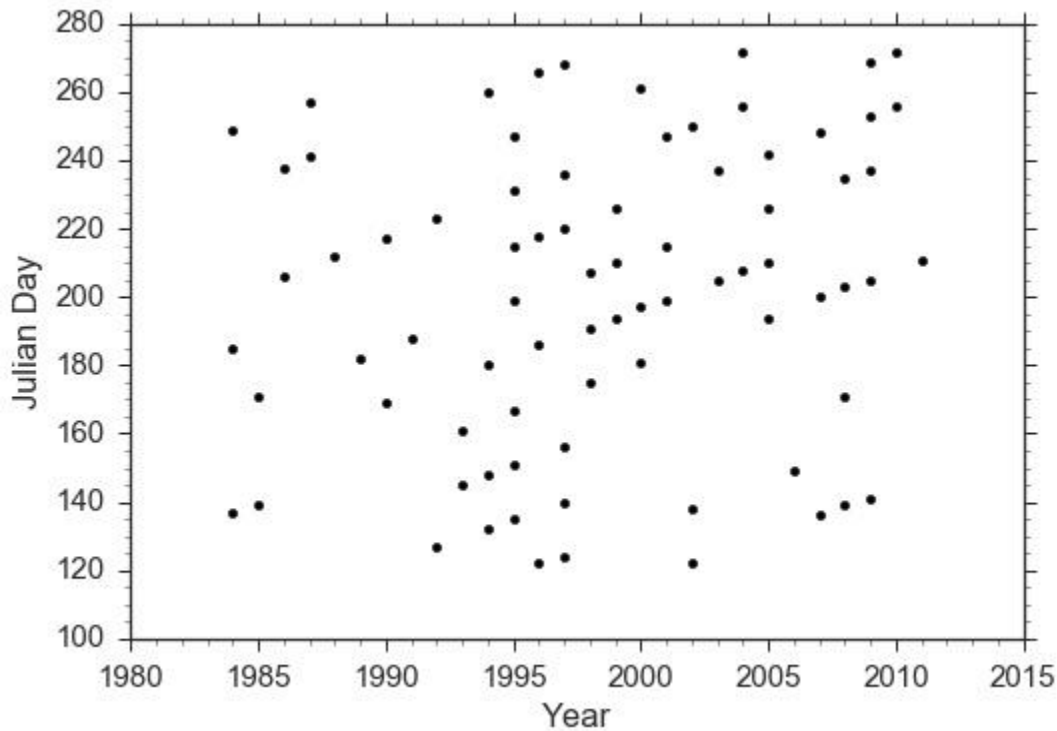


Figure 5. Dates of Landsat scenes used for analysis.

Since grassland were the target of interest for the remotely sensed data, trees were masked out of all images. A 1 m LiDAR digital elevation model (DEM) collected in the spring of 2008, along with the first return point cloud was downloaded from the International Water Institute (IWI) (<http://www.iwinst.org/>). Using ArcGIS the point cloud was turned into a digital surface model (DSM), and then by subtracting the DSM by the DEM feature heights were acquired. Any pixel with a height above or equal to 1.83 meters was then extracted and were used as a mask to remove trees from all images.

Vegetation Indices

Four vegetation indices were calculated: NDVI, NDII, RGR and SWIR32. These were chosen as functional indicators as follows: NDVI is a measure of photosynthetic potential; NDII is a measure

of vegetation water content; RGR is a measure of vegetative stress; and SWIR32 is a measure of bare soil. Table 1 shows the band math implemented to calculate each index for the Landsat 5 band combinations. Trajectories of mean VI values through all pixels for each image are shown in Figure 6.

Table 1. Vegetative indices and associated formulas.

Index	Formula
NDVI (Normalized Difference Vegetation Index)	$\frac{R_{830} - R_{660}}{R_{830} + R_{660}}$
NDII (Normalized Difference Infrared Index; Hardisky and Smart 1983)	$\frac{R_{830} - R_{1650}}{R_{830} + R_{1650}}$
RGR (Red-Green Ratio; Sims and Gamon 2002)	$\frac{R_{660}}{R_{560}}$
SWIR32 (Short Wave Infrared Reflectance 3/2 Ratio; Guershman et al., 2009)	$\frac{R_{2215}}{R_{660}}$

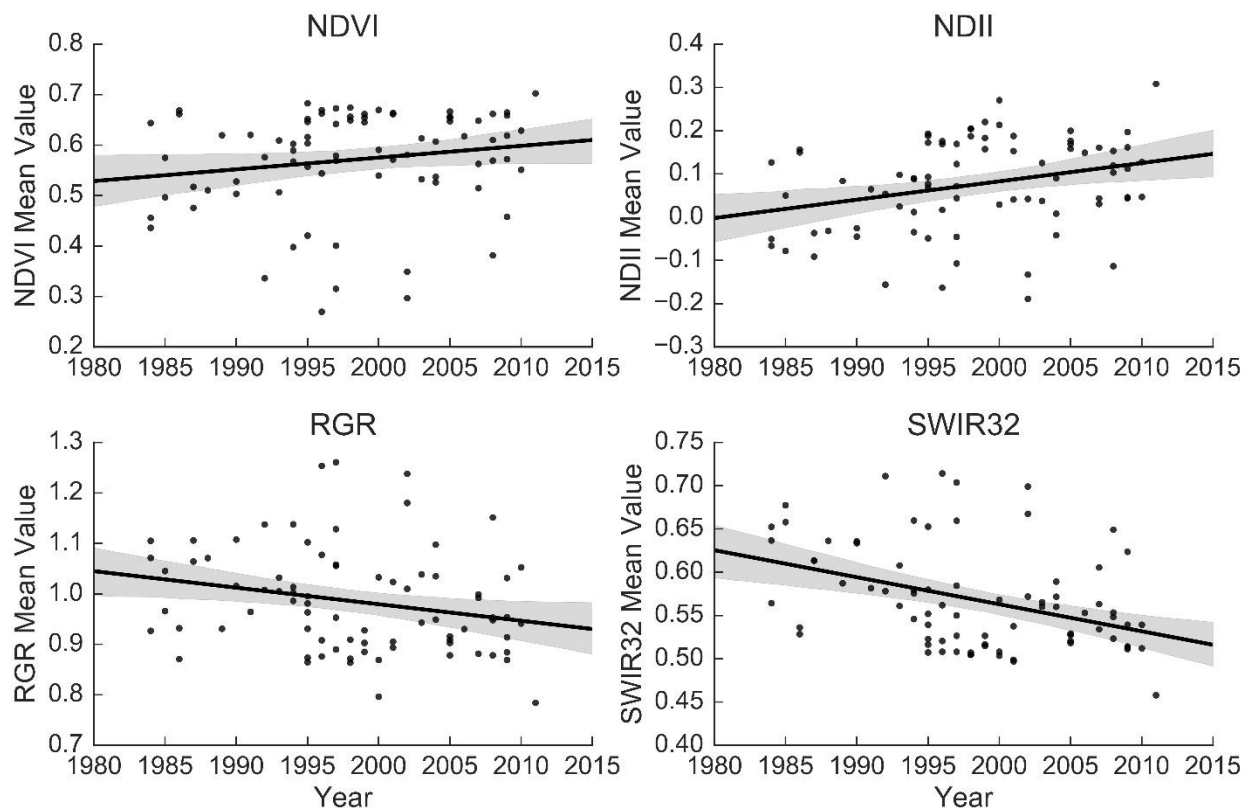


Figure 6. Mean VI values per image for NDVI, NDII, RGR and SWIR32. Grey shading shows 95% confidence intervals.

Climate

Daily climate data from McLeod, ND which is approximately 5 km from the center of the SNG was downloaded from the weather warehouse (<https://weather-warehouse.com/>). For each year over the study period precipitation and growing degree days (GDD) were aggregated into annual sums, and seasonal sums. Winter included December, January and February; spring included March, April and May; summer included June, July and August; and fall included September, October and November. All precipitation is measured as liquid water, therefore snowfall is reported as mm of liquid water. Years that were missing more than 10% of the daily values were excluded

from analysis, which amounted to two years removed from analysis. To examine significant trends in precipitation and GDD both annually and seasonally, linear regression was used.

Composite Index

A composite index (CI) that combined NDVI, NDII, RGR and SWIR32 in a logical functional relationship was created. Figure 7 shows a flowchart detailing how the CI was created and the rationale behind it. First, all the data from the original indices was normalized with the following equation:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where x_{norm} is the normalized pixel value, x is the original pixel value, x_{min} is the minimum index value across the entire time series and x_{max} is the maximum index value across the entire time series. It was important to normalize pixel values so that all data were scaled from 0 to 1 and no negative values occurred.

Second, a logical functional basis for combining the individual normalized VIs was defined based on known response of individual indices to vegetation properties and behavior (Figure 7).

The NDVI is positively correlated with photosynthetic capacity; the NDII is positively correlated with vegetation moisture content, which is also predominantly correlated with photosynthetic capacity; the RGR is positively correlated with stress and negatively correlated with photosynthetic capacity; while the SWIR32 is negatively correlated with high levels of non-photosynthetic vegetation, and high values tend to indicate more bare soil.

Based on these responses, it is possible to formulate a composite index that combines normalized $NDVI_n$ and $NDII_n$ with inverse normalized $iRGR_n$ and $iSWIR32_n$ such that this index is positively correlated with good grassland condition and growth capacity.

The CI is calculated by a simple sum of the normalized $NDVI_n$, $NDII_n$ and inverse normalized $iRGR_n$ and $iSWIR32_n$.

$$CI = NDVI_n + NDII_n + iRGR_n + iSWIR32_n \quad (2)$$

CI values that are larger should now represent preferable growing conditions than values that are smaller. It is important to note that best growing conditions does not necessarily mean a healthy ecosystem as invasive species may also have a large CI value. To evaluate the effectiveness of the CI to simulate the original four indexes correlation coefficients were evaluated as described in Stage 1 of the conceptual framework.

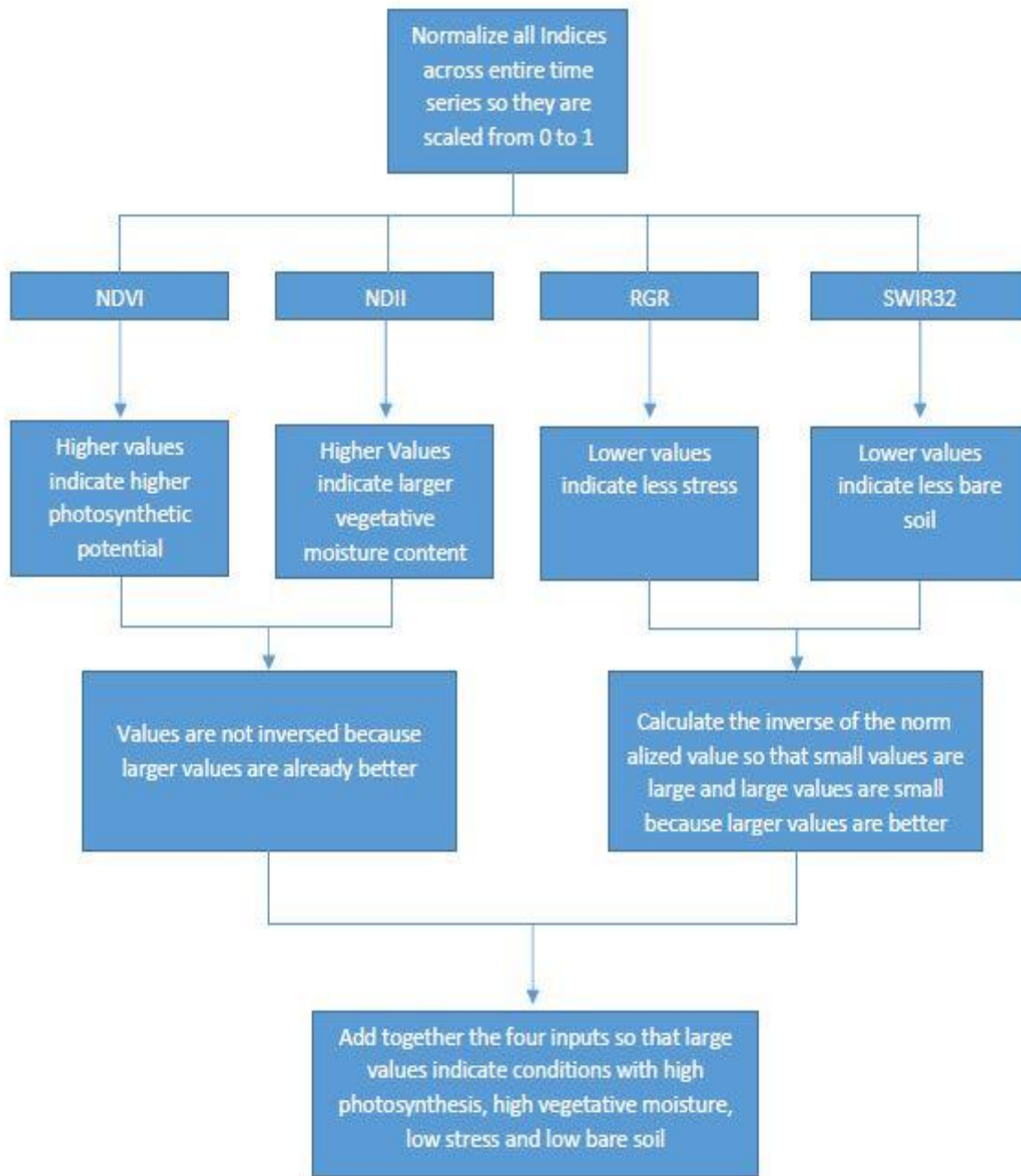


Figure 7. Flowchart diagramming the conceptual model used to combine the four original indices together into the CI.

Pearson's Correlation Coefficients

As previously described, Pearson's correlation coefficients were evaluated on a per pixel basis between all possible VI combinations. Coefficients were evaluated over the Complete Time Series, the Early Season, Peak Summer and Late Season. Maps which display coefficients for each VI combination are shown for each of the four time segments. Additionally, to highlight locations where correlations between certain VI's are low, National Agriculture Imagery (NAIP) (<https://www.fsa.usda.gov/programs-and-services/aerial-photography/imagery-programs/naip-imagery/>) imagery and a 1-meter resolution LiDAR digital elevation model (DEM) are utilized to offer insights.

Differenced Conditions

In order to establish the initial basis for the analysis of potential change in grassland properties on the SNG, a simple comparison of VI values between two time periods was evaluated. Two time periods were selected to evaluate differenced conditions per index, 1984 – 1995 (time period one) and 2004-2011 (time period two). The time periods were separated by a gap in order to make the comparison as independent of short term annual climate fluctuations as possible. Images taken from the same time of year were used for comparison in order to remove seasonal variation as much as possible. Only the months of May, July and August were used for the comparison due to lower image availability in June and September in the two periods. For each time period 13 images were compared in total, 4 images from May, 5 images from July and 4 images from August. The mean value per pixel for all 13 images per time period was then calculated to determine average conditions per time period, and then the average conditions per time period were differenced by

subtracting time period one from time period two. Variation in the differenced values by landform and GAP class were then explored by comparing box plots of differenced values.

Regression Analysis

To examine trends in VI's regression analysis was implemented in three ways: 1) simple linear regression; 2) multiple regression; and 3) a random forest regression. Simple regression was relied upon to determine how slopes and R^2 values vary in association with a variety of independent variables, and through different times of the growing season. Multiple regression was implemented to determine overall model fits by evaluating R^2 values, and random forest regression was used to evaluate the importance of different independent variables to predict VI values.

Simple Linear Regression

Four independent variables are hypothesized to be the most influential for causing VI change, and they include the amount of days elapsed within the time series itself, termed 'Running Days', antecedent precipitation (APRCP), antecedent growing degree days (AGDD) and grazing pressure.

In order to assess changes which have taken place for each of the five indices through time linear regression was used with the index value (for each pixel) as the dependent variable and time as the independent variable. Time in this case is expressed as the amount of days which has elapsed between the start of the time series (05/17/1984) and the last day of the time series (07/31/2011).

In total there were 9,199 days in the time series. Regression models were fit over four time periods:

1. A 'Complete Time Series' model whereby all 79 images in the time series are included in the regression.
2. An 'Early Season' model where only images acquired in May or June are included.

3. A 'Peak Summer' model where only images acquired between July 1st and August 20th are included.
4. A 'Late Season' model where only images acquired between August 21st and September 30th are included.

Since the SNG is a mixture of cool season C₃ grasses which are most productive in the early growing season and C₄ grasses which are most productive in the peak of summer, models which are segmented by time should help elucidate locations where (VI) response varies by season. Three specific areas will be utilized to explore this: (1) the Viking prairie (Figure 3) which is ungrazed and consists primarily of native C₄ plants such as big bluestem and Indian grass; (2) the East Durler unit which is also ungrazed and consists of native C₄ plants, but with a larger mix of C₃ forbs than the Viking prairie; (3) the West Durler unit which has historically been grazed and is infested with leafy spurge and Kentucky bluegrass. How these three locations vary temporarily in VI change will be assessed. Slopes for the Running Days regression are expressed as change over the Complete Time Series, or slopes per 9,199 days.

Similar to how regression was used with time as the independent variable, regressions which implement APRCP as the independent variable were also completed. APRCP is defined as the accumulated precipitation in mm from February 1st to the image acquisition date for images acquired in May, and accumulated precipitation two months prior to image acquisition for all other months. February 1st was used as the start of accumulation for May images so that snowpack from the winter would be included. Regressions were once again run for all four time periods. Slopes are expressed in change per pixel per index value per 200 mm of APRCP.

In addition to APRCP, the influence of AGDD was also explored. AGDD's were calculated for each day as:

$$(T_{max} - T_{min})/2 - Base\ T \quad (3)$$

where *Base T* is 0°C, *T_{max}* is the maximum temperature recorded in a day and *T_{min}* is the minimum temperature recorded in a day. Base temperatures are usually calculated from physiological thresholds associated with differences in thermal response among plant species having different photosynthetic pathways. The base temperature for C₃ species is usually around 0 degrees C. The base temperature for C₄ grasses and crops is usually around 8 - 10 degrees C and these species are usually intolerant of frost or freezing. However, in this highly seasonal continental climate with growth confined to a 110-120 day warm period it was not necessary to make any distinction so 0 degrees C was used for all species. The C₄ species would not start growing until their real base T was met.

In order to assess grazing pressure on index values regressions were implemented with grazing pressure, expressed as ha/number of cattle, as the independent variable. Historical grazing records were provided by the SNG as the pressure per allotment per year. Allotments are distinct management units (Figure 3) on the SNG which are fenced off and have different grazing pressures. Pixels within each individual allotment were extracted, and the appropriate grazing pressure depending on the year of image acquisition assigned. Mean grazing pressure per year across all allotments has been highly variable in the first half of the time series, but relatively consistent in the second half (Figure 8).

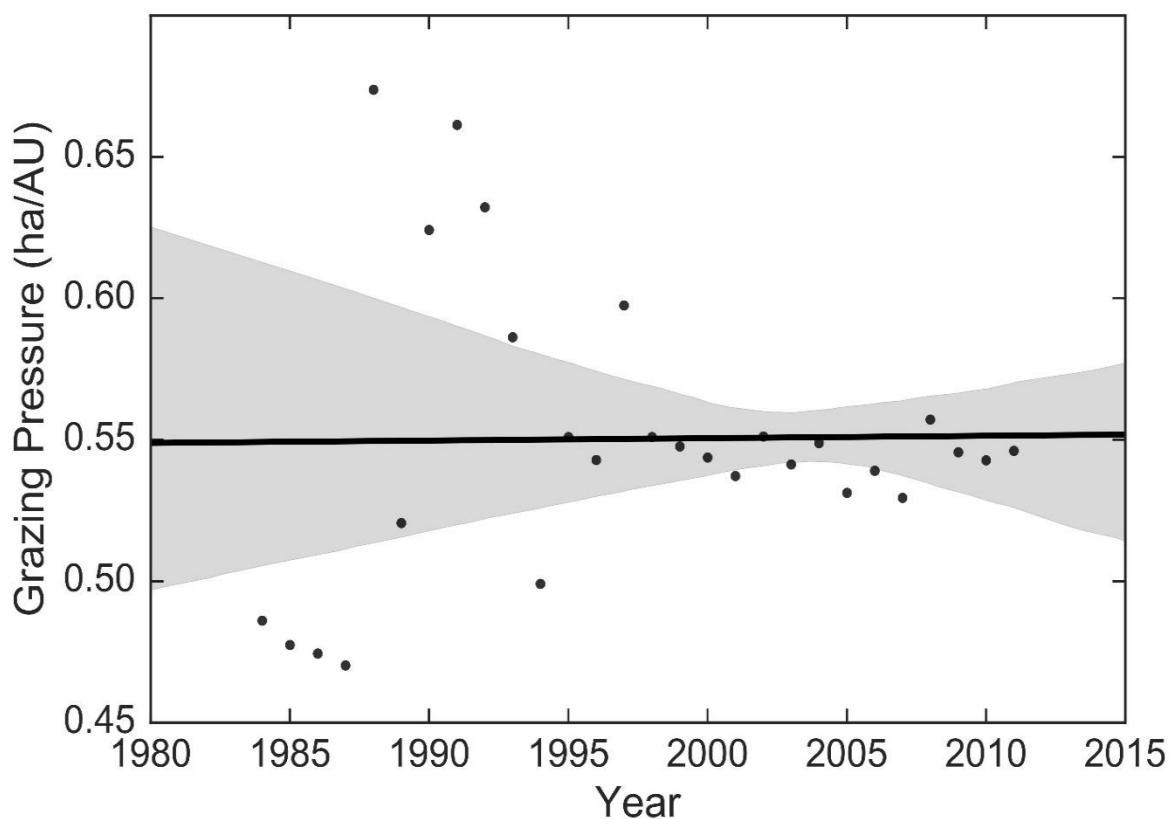


Figure 8. Mean grazing pressure per year (ha/Animal Units) across all allotments on the SNG. Grey shading indicates 95% confidence.

Maps which display significant pixels ($\alpha \leq 0.05$), slopes and adjusted R^2 (for all independent variables) per pixel are used throughout this analysis to highlight how individual pixels have changed for all four time periods. For the rest of this analysis whenever R^2 values are shown it is adjusted- R^2 values that are being presented. To further analyze spatial variation across landforms and species compositions, box plots of slopes and R^2 values were evaluated.

Multiple Regression

In addition to analysis involving simple linear regression, multiple regression was used to evaluate how multiple independent variables may be interacting to influence VI response through time. Variables in the multiple regression included Running Days, APRCP, AGDD, grazing pressure, available water storage (AWS) in the top 150 cm of the soil profile, soil organic carbon (SOC) in the top 150 cm of the soil profile, percent of soil which is sand (mineral particles 0.5 to 2 mm expressed as a percentage weight of soil fraction), percent of soil which is silt (mineral particles 0.002 to 0.05 mm), percent of soil which is clay (mineral particles < 0.002 mm), soil drainage, landform and GAP vegetation class.

Of all the independent variables, soil drainage, landform and the GAP vegetation class are dummy variables. Soil drainage ranges from excessively well drained to poorly drained. All soil data were provided by SSURGO (https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcs142p2_053627), and soil types per pixel were determined by intersecting the centroid of a pixel to SSURGO polygons. Multiple regressions were run sequentially to determine how R^2 values varied as more variables were included, and to determine which variables were the most important. On the first sequence, Running Days, APRCP, AGDD and grazing pressure were included in the model. On the second sequence all variables which were not dummy variables were included (everything but soil drainage, landform and GAP class). On the third sequence all variables were included.

Multiple regressions were also run per pixel and variation in R^2 values by landform and GAP class were again compared with box plots.

Random Forest Regression Model

Decision tree models have not been widely used within the remote sensing field despite their non-parametric approach (Kulkarni and Lowe 2016). Decision trees are predictive models which attempt to identify a target value based on predictor values. Target values are the decision trees “leaves” and predictor values are the “branches”. Decision trees attempt to determine a target value based on the predictor values by evaluating a series of ‘Yes’ and ‘No’ questions to dictate how to reach a conclusion about what target value may be.

There are two types of decision trees: decision tree regressions, and decision tree classifiers. For decision tree regressions the target value is a continuous variable (such as a vegetation index) and for decision tree classifiers the target value is discrete (such as a land cover type). In order to determine if a question is a ‘Yes’ or a ‘No’ in a decision tree regression a linear regression model is fit to the target from independent variables in the model. The variable with the lowest mean square error (MSE) is used to ‘split’ the tree. In a decision classifier a tree is split based on the information gain (the feature which provides the model the most information) rather than MSE among the independent variables. In both cases, decision trees will continue splitting until the correct classification is predicted, or the user predefines the stopping criteria.

A random forest model is a type of decision tree which injects randomness into the dataset in two ways. The first is by removing random samples from the dataset to build multiple decision trees (forests), and then averaging across all trees to determine the best split option. The second way randomness is included is by bootstrapping the independent variables themselves, which is to say the individual trees are built with different independent variables. When using decision trees it is important to split the dataset into a training and testing set. It is common to train the model on 70% of the data and test on 30%. If R^2 are not similar between the training and testing the model

is either overfitting or under fitting and parameters need to be tuned. To learn more about how a decision tree and random forest model operates see Kulkarni and Lowe (2016).

This study uses a random forest regression to evaluate how well the same independent variables used in the multiple regression (with the exception of Running Days) can predict VI values. In other words, the target variable was the VI value and the predictor variables were the independent variables already discussed. Note that target variables are the VI value for every pixel, and every image within the time series. For example, when evaluating the capability of the random forest model to predict NDVI values, the target variable was the NDVI value for every single pixel across all images, and the associated independent variables for the respective pixel. The same was completed for NDII, RGR, SWIR32 and the CI. Random forest models were evaluated over all four time segments previously discussed.

One advantage of random forest models to linear or multiple regression models is that not only are R^2 values provided for model fits, but the importance of each independent variable relative to the others is also calculated. Feature importance's always sum to 1, and the independent variable with the largest importance is the feature that provided the most information to the model. This allowed for comparison between indices as to which variables were the most influential.

Table 2 provides a list of all acronyms that are used throughout this study.

Table 2. Acronyms used throughout the study.

Acronym	Meaning
VI	Vegetation Index
APRCP	Antecedent Precipitation
AGDD	Antecedent Growing Degree Days
NDVI	Normalized Differenced Vegetation Index
NDII	Normalized Differenced Infrared Index
RGR	Red-Green Ratio
SWIR32	Shortwave infrared 3/2 Index
CI	Composite Index
TS	Time Series
ES	Early Season
PS	Peak Summer
LS	Late Season
DP	Deltaic Plain
HS	Hummock and Swale
SD	Sand Dunes
MTGP	Mesic Tallgrass Prairie
WMTGP	Wet Mesic Tallgrass Prairie
BNW	Bluestem-Needlestem-Wheatgrass
PHP	Planted Herbaceous Perennial
SP	Sand Prairie

CHAPTER IV

RESULTS

Climate

Linear regression was used to evaluate trends in precipitation and growing degree days (GDD) between 1984 – 2011 based on the McLeod weather station data, both annually and seasonally. For precipitation, trends were only significant annually and in the summer. Figure 9 shows scatter plots of regression results for significant precipitation trends with the line of best fit drawn through and 95% confidence intervals shown in the shaded areas. Precipitation has increased by 7.05 mm between 1984 and 2011 annually and 3.8 mm in the summer months. For GDD, the only significant trend was for spring (Figure 10). In the spring, there has been a decrease of 7.39 GDD between 1984 – 2011. Annually, GDD decreased by 12.12 GDD per year but this trend was not significant.

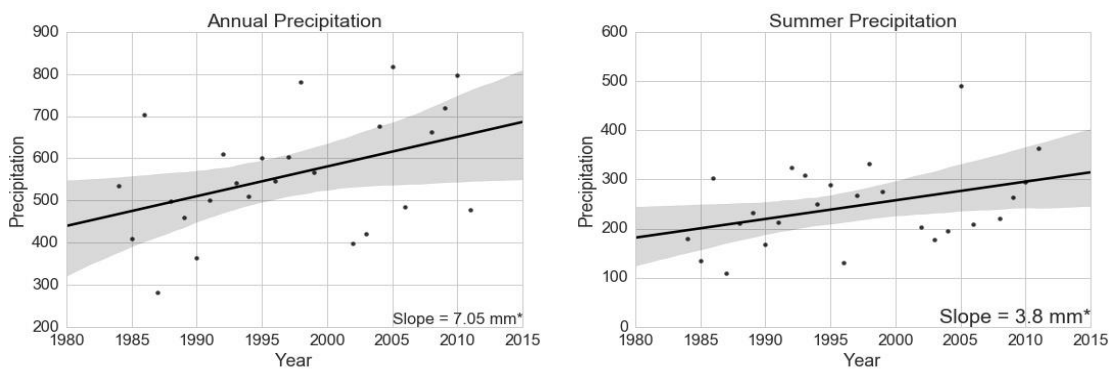


Figure 9. Annual and summer precipitation regression results. Significant slopes are expressed with a *.

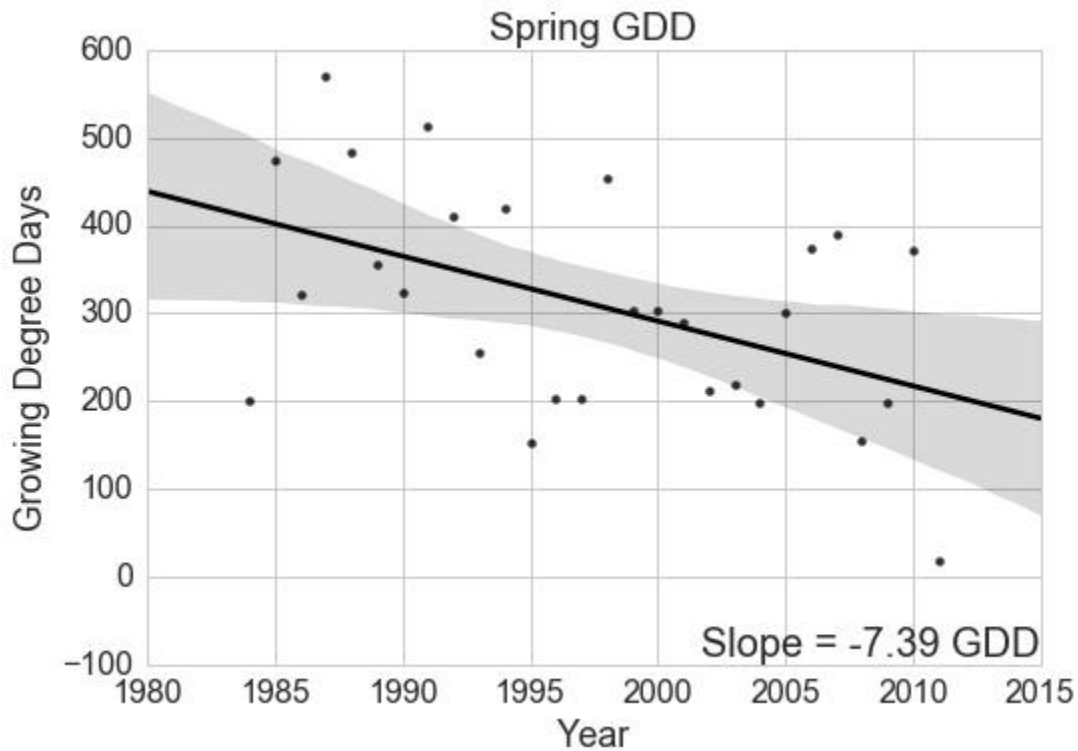


Figure 10. Spring GDD regression results. Significant slopes are expressed with a *.

Correlation between Indexes

Pearson’s correlation coefficients were evaluated on a per pixel basis for all VI combinations to determine if spatial variation existed between any two particular VI’s. Based on the previously outlined ‘conceptual framework’, positive correlations were expected between the CI and all other VI’s. Positive correlations were also expected between NDVI and NDII, and RGR and SWIR32, and negative correlations are expected when comparing either NDVI or NDII to RGR or SWIR32. There were strong positive correlations between NDVI and NDII across the SNG (> 0.8), but lower correlations (0 – 0.6) in specific locations (Figure 11). NAIP imagery was used to examine this variation in the spatial pattern and distribution of correlation coefficients of the three specific

locations, labeled by the subpanels 'A', 'B', and 'C' in Figure 11. Figure 12 compares NAIP imagery to the correlation coefficients for NDVI and NDII in the locations of each subpanel denoted in Figure 11. In Figure 12 NAIP imagery is shown on the left and correlation coefficients in the Peak Summer are shown on the right. Subpanel relation in Figure 12 to Figure 11 are indicated in each row. Each location comparison is focused on wetland areas with surrounding oaks where correlation coefficients are low (>0.4). This is likely due to high NDII values coupled with low NDVI values because standing water is suppressing vegetative growth.

There was very strong negative correlation between NDVI and RGR (Figure 13). In select locations correlation is weaker ($>0 - -0.4$) and these locations are highlighted by the subpanels denoted by the letters 'A', 'B' and 'C'. The spatial patterns in the locations of these subpanels are explored in detail in Figure 14 in relation to a 1-meter resolution LiDAR DEM. Correlation coefficients are often weakest for the NDVI – RGR comparison when elevations are highest, although coefficients were still negative.

NDVI – SWIR32 correlation coefficients exhibit a similar spatial pattern to the NDVI – RGR correlations with an association between lower correlation coefficients and higher elevations. Coefficients are also very similar to NDVI – RGR, which is that on the high elevations NDVI – SWIR32 coefficients are between $-0.4 - -0.8$ and usually between $-0.8 - -1.0$ on the lowlands.

NDII – RGR (not shown) and NDII – SWIR32 (not shown) correlation maps show very similar results to NDVI –RGR and NDVI – SWIR32.

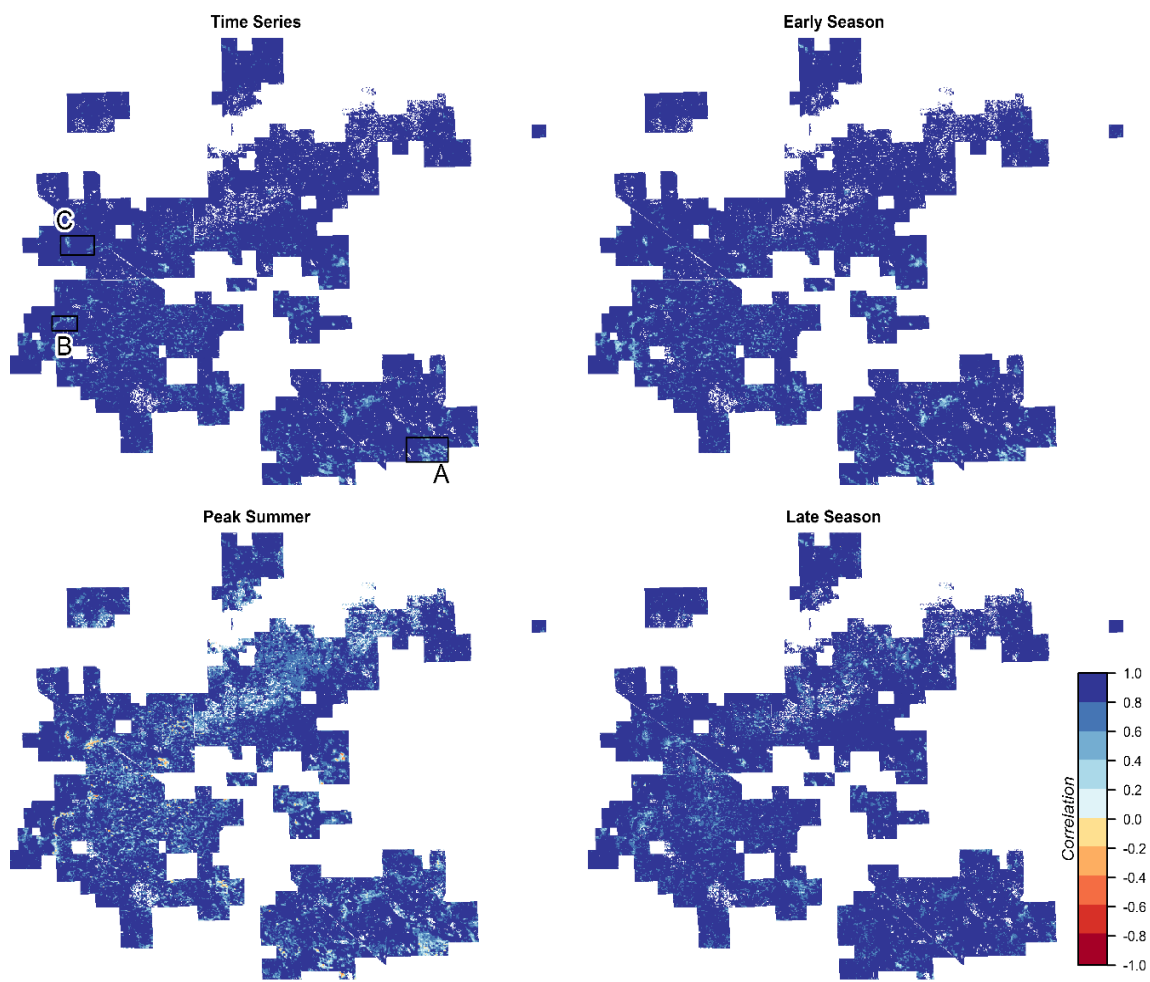


Figure 11. Correlation coefficients for NDVI and NDII. Subpanels denoted by the letters 'A', 'B' and 'C' are the locations selected for detailed comparison in Figure 12.

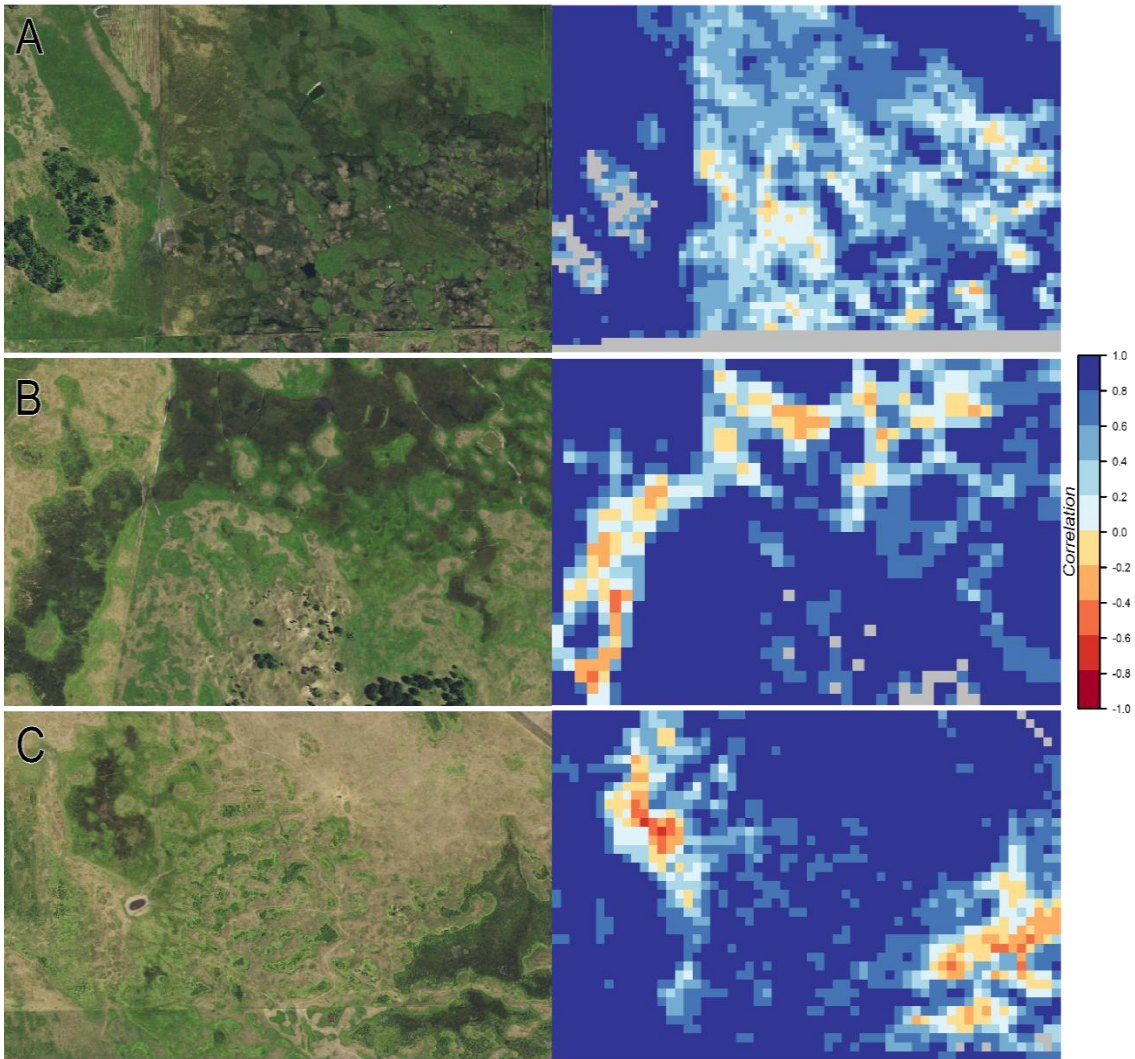


Figure 12. NAIP imagery comparisons with NDVI – NDII correlation coefficients for the Peak Summer. NAIP imagery is shown on the left and correlation coefficients on the right in the same location. Rows marked with the letters ‘A’, ‘B’ and ‘C’ relate to the locations on the SNG shown in Figure 11.



Figure 13. Correlation coefficients for NDVI and RGR. Subpanels denoted by the letters 'A', 'B' and 'C' are the locations selected for detailed comparison in Figure 14.

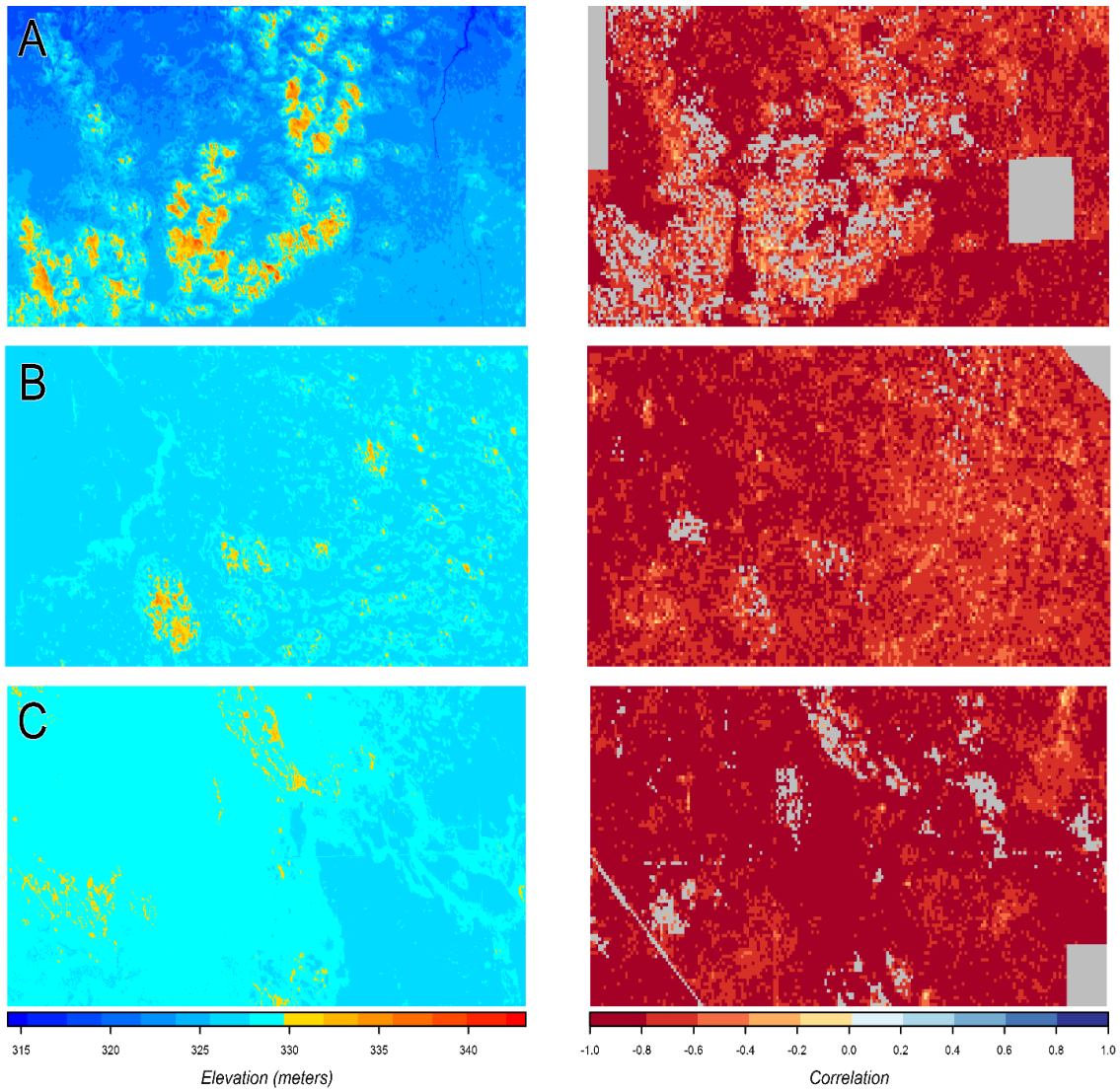


Figure 14. DEM imagery comparisons with NDVI – RGR correlation coefficients for the Late Season. DEM imagery is shown on the left and correlation coefficients on the right in the same location. Rows marked with the letters ‘A’, ‘B’ and ‘C’ relate to the locations on the SNG shown in Figure 13.

RGR and SWIR32 exhibited strong positive correlations across most of the SNG with lower values in the Peak Summer and the Late Season across the sand dunes and hummock and swale (Figure 15). Subpanels highlight where patches of weak positive and weak negative correlations for RGR – SWIR32 were associated with elevation (Figure 16).

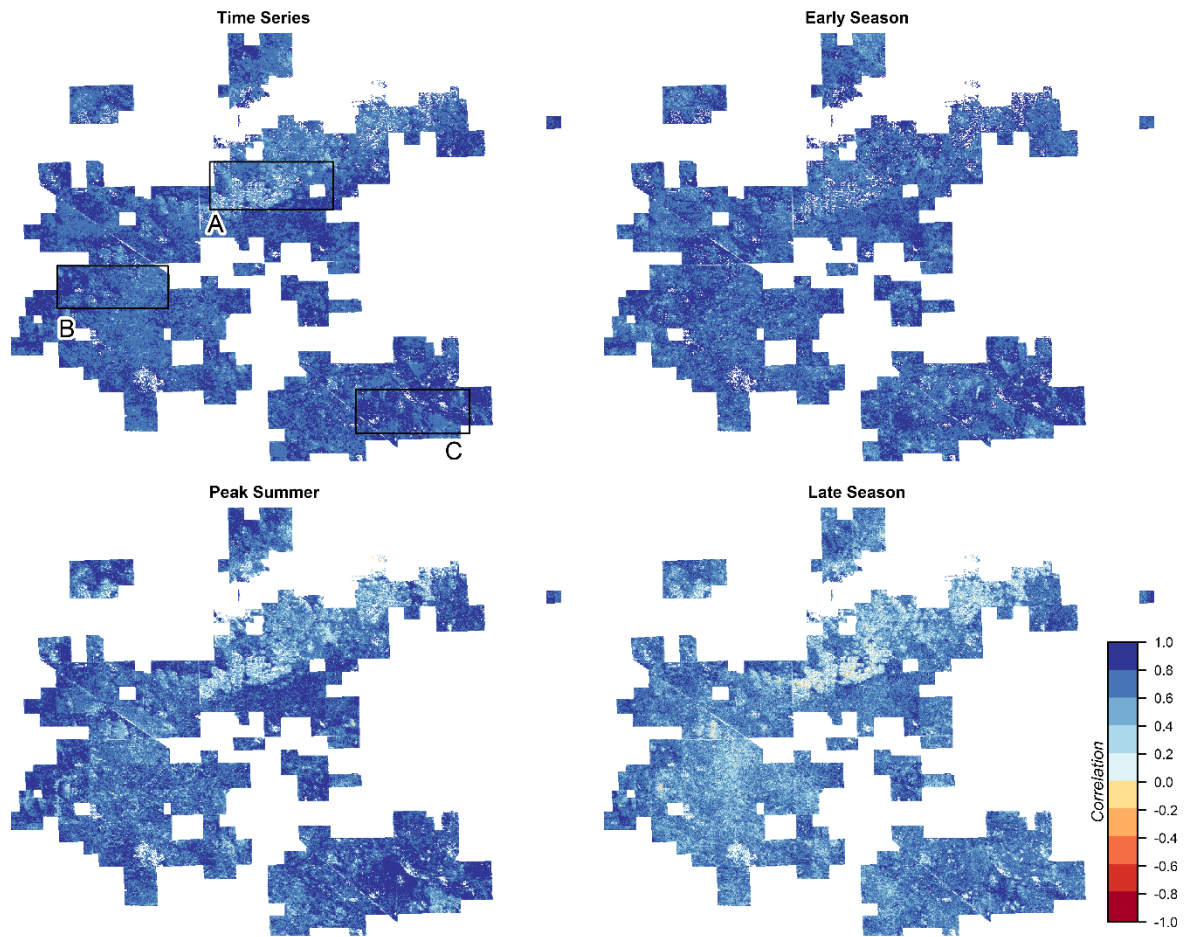


Figure 15. Correlation coefficients for RGR and SWIR32. Subpanels denoted by the letters 'A', 'B' and 'C' are the locations selected for detailed comparison in Figure 16.

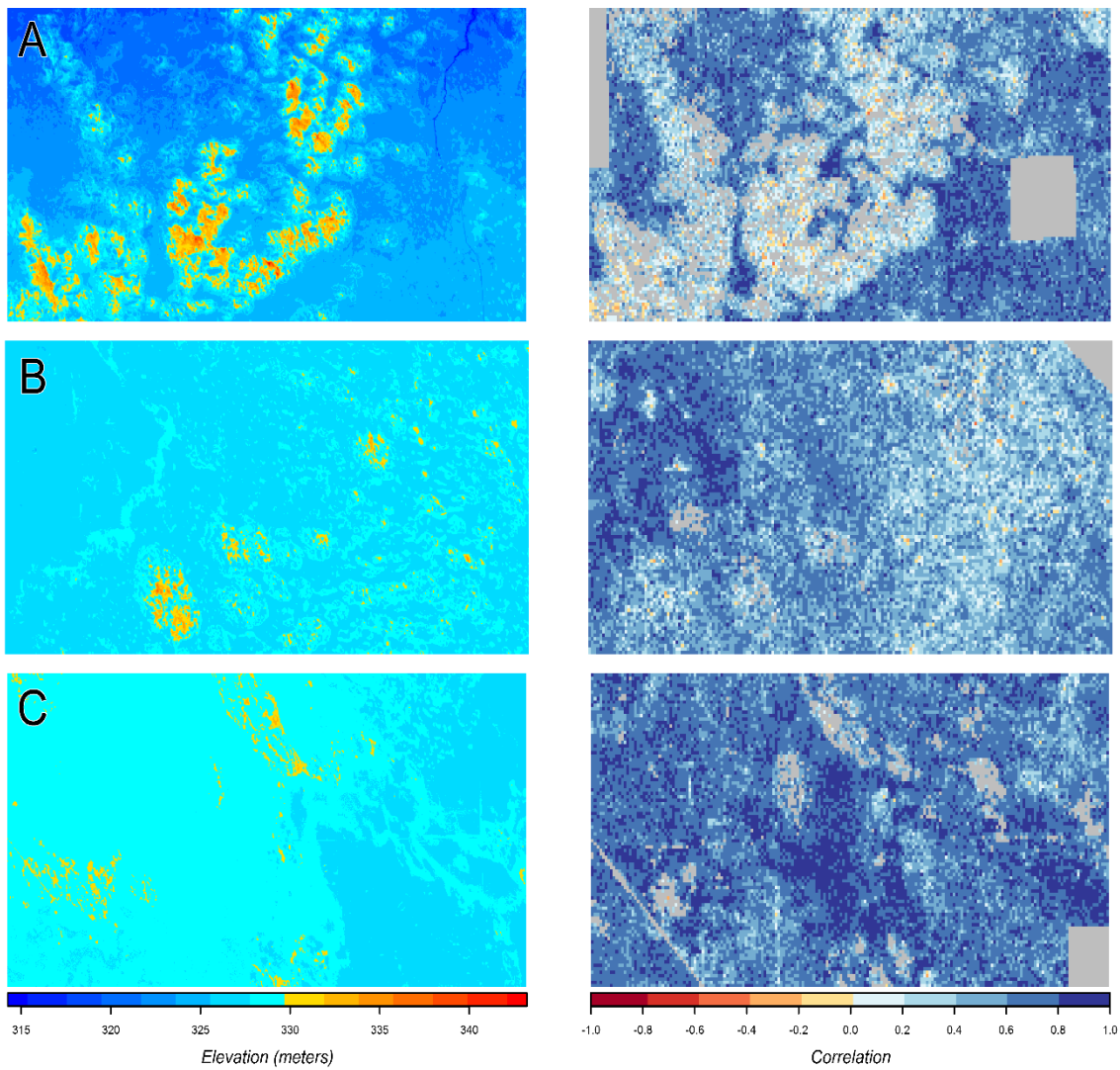


Figure 16. DEM imagery comparisons with RGR – SWIR32 correlation coefficients for the Late Season. DEM imagery is shown on the left and correlation coefficients on the right in the same location. Rows marked with the letters ‘A’, ‘B’ and ‘C’ relate to the locations on the SNG shown in Figure 15.

Correlations between CI and its constituent VI's (not shown) produced values between 0.8 and 1.0 for NDVI and NDII and -0.8 and -1.0 for RGR and SWIR32 for the Complete Time Series, Early Season and Peak Summer. In the Late Season coefficients drop to -0.6 – 0.8 in small areas in the hummock and swale and sand dunes. Spatial patterns where this occurs are nearly identical for the CI – RGR and the CI - SWIR32 comparison (not shown). In general, the correlations between indices match expectations in that they respond as hypothesized, but also show deviations from the typical response which may be helpful in discrimination of local changes in vegetation condition.

Differenced Conditions

Image differencing compared VI values for two time periods: 1984 – 1995 (time period one) and 2004 – 2011 (time period two) for each of the five indexes in order to determine if changes in VIs had occurred over the time frame of the study. The majority of pixels across the SNG show significant change in values between period 1 and period 2 for constituent VIs (Figure 17) and the CI (Figure 18). It is important to note that as NDVI and NDII increase, greenness and vegetation moisture content increase respectively. When RGR and SWIR32 decrease, stress and bare soil decrease respectively. Therefore, more negative values for RGR and SWIR32 are actually 'better conditions'. Areas identified by the author as wetlands exhibit small or even negative differences between periods for NDVI but mostly positive differences between periods one and two for NDII (Figure 17).

The differences in CI between the two time periods include locations where individual VI differences have the same direction of change which enhances the change in CI, and where individual VI differences occur in opposite directions the differenced CI values are diminished.

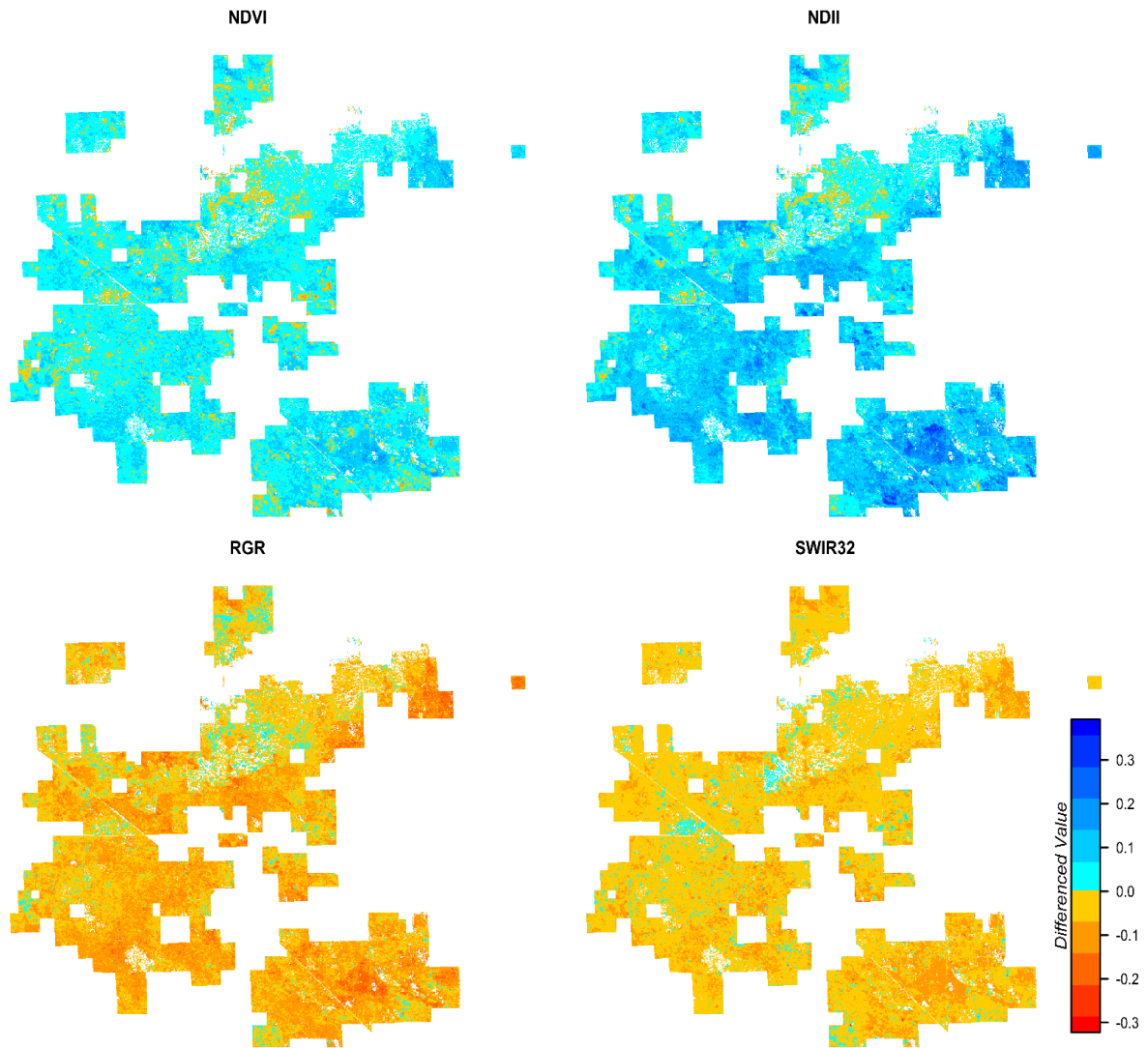


Figure 17. NDVI, NDII, RGR and SWIR32 differenced images.

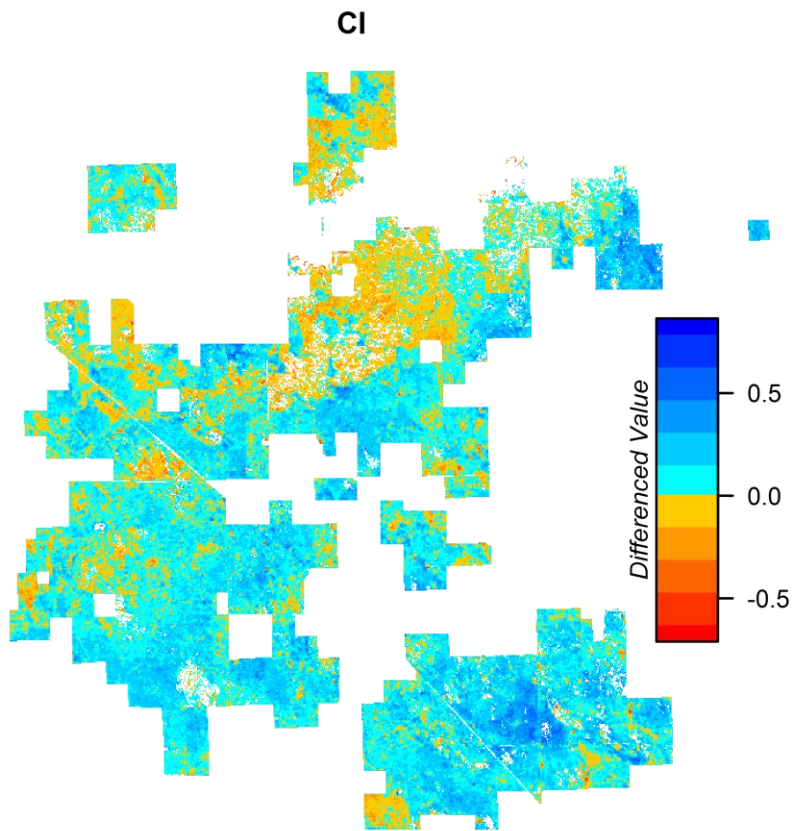


Figure 18. Composite Index (CI) differenced image.

Comparisons of differenced images across landforms and GAP classes using boxplots show that differences are relatively small except for in outlier pixels (Figure 19, 20). In general, the deltaic plain and hummock and swale landforms have larger median differenced values between periods one and two than the sand dunes landform for the CI, NDVI and NDII. For RGR and SWIR32 the deltaic plain and hummock and swale landforms have smaller median values than the sand dunes (Figure 19).

Comparison of the difference images by GAP class shows that the MTGP, WMTGP and wetlands have slightly larger median values than the BNW, PHP and SP for the CI (Figure 19). For NDVI, there is little variation in GAP class. For NDII the same trends as the CI are reflected, but they are more exaggerated. It is particularly interesting that NDII slopes are so large in wetlands but rather small in wetlands for NDVI. This coupling of a low NDVI and larger NDII also occurred when comparing correlation coefficients. For RGR, the same trends as the CI and NDII again occur (but with opposite direction). There is little variation in differenced values by GAP class for SWIR32.

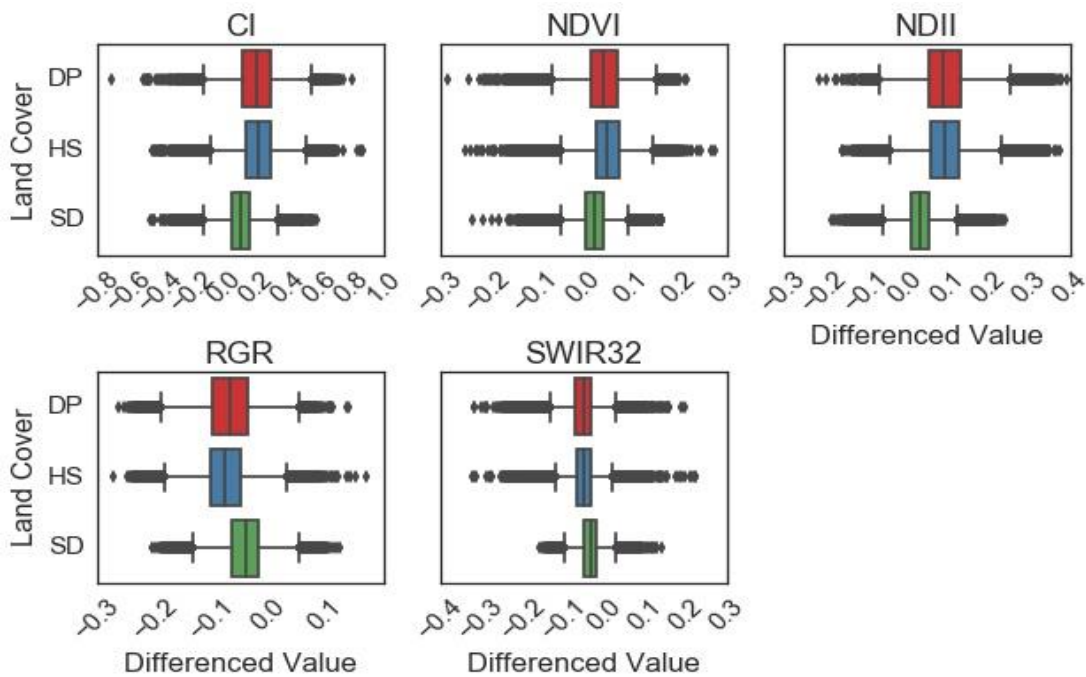


Figure 19. Boxplots of differenced values by landform for each VI. DP = Deltaic Plain; HS = Hummock and Swale and SD = Sand Dunes.

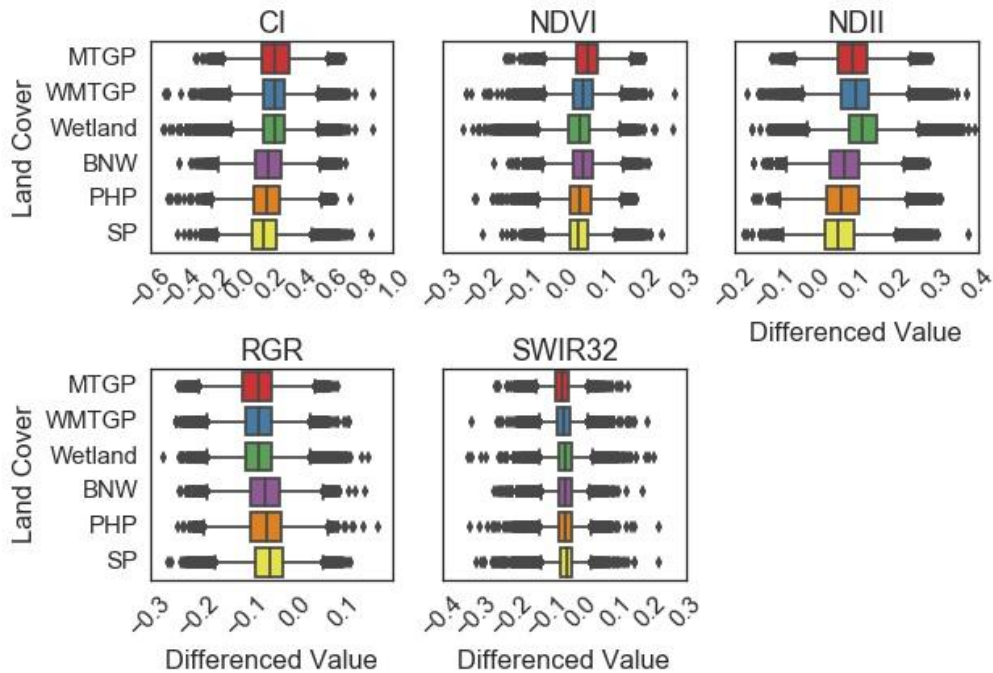


Figure 20. Boxplots of differenced values by GAP class for each VI. MTGP = Mesic Tallgrass Prairie; WMTGP = Wet Mesic Tallgrass Prairie; BNW = Bluestem-Needlestem-Wheatgrass; PHP = Planted Herbaceous Perennial and SP = Sand Prairie.

Overall, the results of the comparison of VIs between periods one and two show larger increases in NDVI, NDII and CI, and larger decreases in RGR and SWIR32 for the deltaic plain and hummock and swale landforms than the sand dunes. Variation in differences values between NDVI and NDII occurs only in wetland areas. However, the results also indicate that the CI is capturing the remotely sensed response from the original four VI's as desired.

This analysis confirms that there are consistent differences in individual and composite VIs between the two time periods. This suggests that there is scope for further detailed analysis of trends and drivers of these differences in subsequent sections. The similarity in responses between NDVI and NDII, and RGR and SWIR32 mean that there is some redundancy among these VI's.

As a result, except for specific seasonal and geographical situations, subsequent analysis will focus only on NDVI, SWIR32 and CI.

Running Days Regression

Simple linear regression was used to examine the trends in NDVI, SWIR32 and CI for the all four time segments. Scatter plots of VI versus time in days illustrate the variation in the slope and quality of regression line of best fit for the pixel for the largest R^2 values through the Complete Time Series for the CI, NDVI and SWIR32 (Figure 21). Table 3 shows regression results for each pixel and VI from the scatter plots.

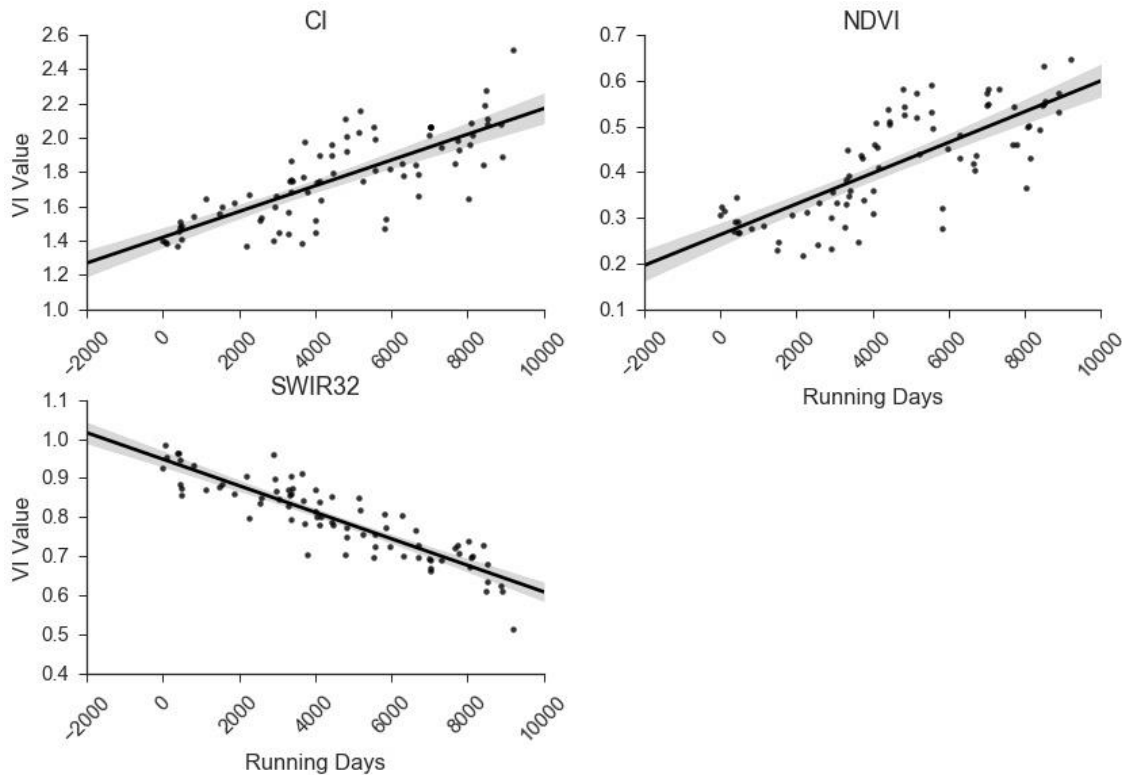


Figure 21. Scatterplots and lines of best fits for the pixel with the largest R^2 values through the Complete Time Series for the CI, NDVI and SWIR32.

Table 3. Regression results for each pixel and VI from the largest R² comparisons in Figure 21.

Index	R²	Slope	RMSE	p-value
CI	0.59	0.69	0.16	0
NDVI	0.58	0.31	0.08	0
SWIR32	0.79	-0.31	0.05	0

Maps which express slopes per pixel for each of the four time series segments were also evaluated for the CI, NDVI and SWIR32. After maps are presented, select box plots of regression results are compared. Lastly, temporal response of NDVI over the Viking prairie and Durler Unit are also compared.

For the CI (Figure 22) and NDVI (Figure 23) slopes are largest in the Peak Summer, for SWIR32 (Figure 24) slopes are smallest in the Peak Summer. In the Early Season many pixels are negative for CI and NDVI and positive for SWIR32. R² values are not shown for CI and NDVI over the Complete Time Series and Early Season as most values are between 0 – 0.1, but are for the Peak Summer and Late Season (Figure 25, 26). R² values are largest in the Peak Summer for CI and NDVI, and the CI has slightly larger values in the late season than NDVI. SWIR32 has the largest R² values in the Peak Summer and Late Season (Figure 27).

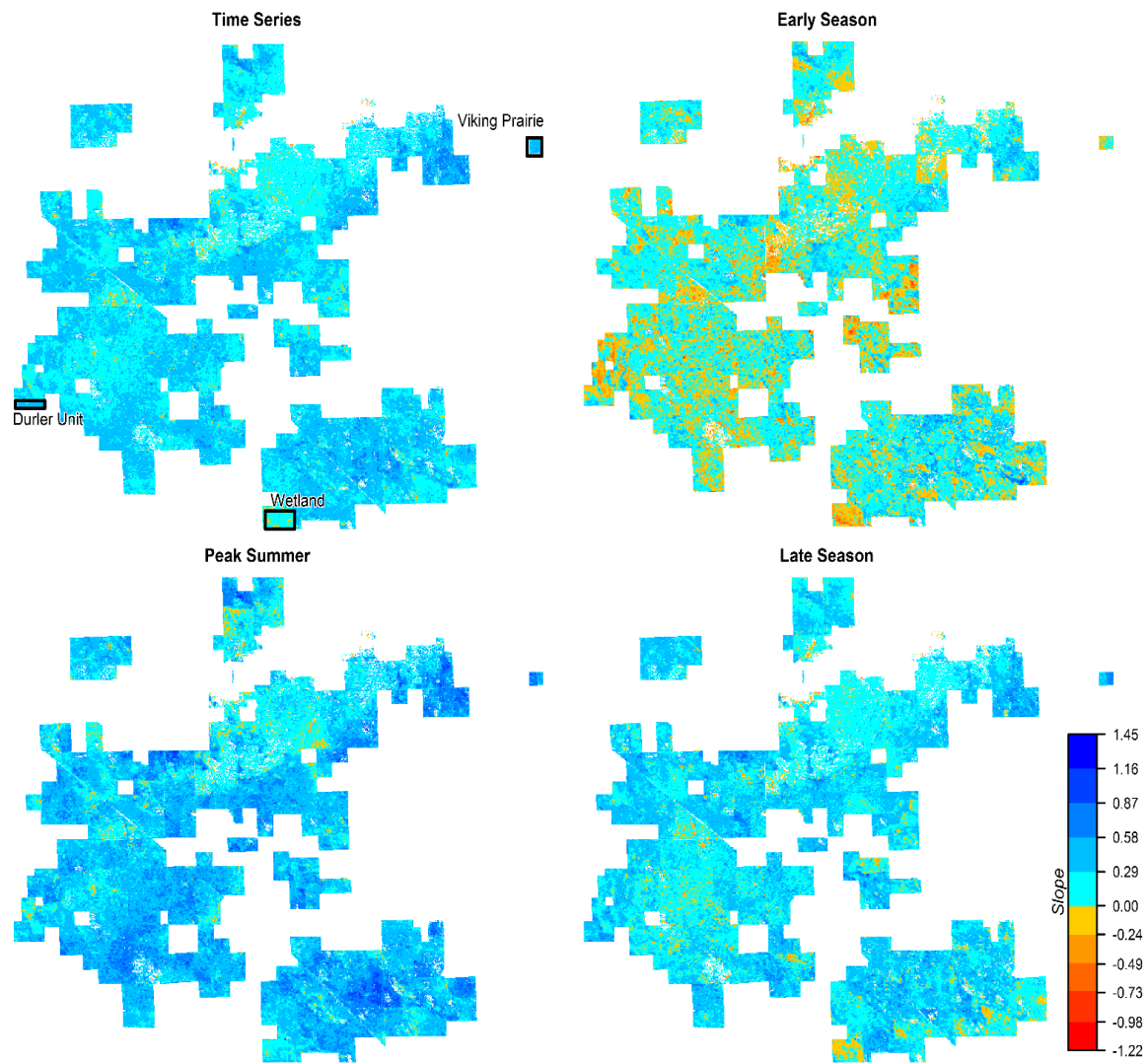


Figure 22. Running Days slopes for the CI through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown. Insets show locations of the Viking Prairie and Durler Units which are used for later analysis

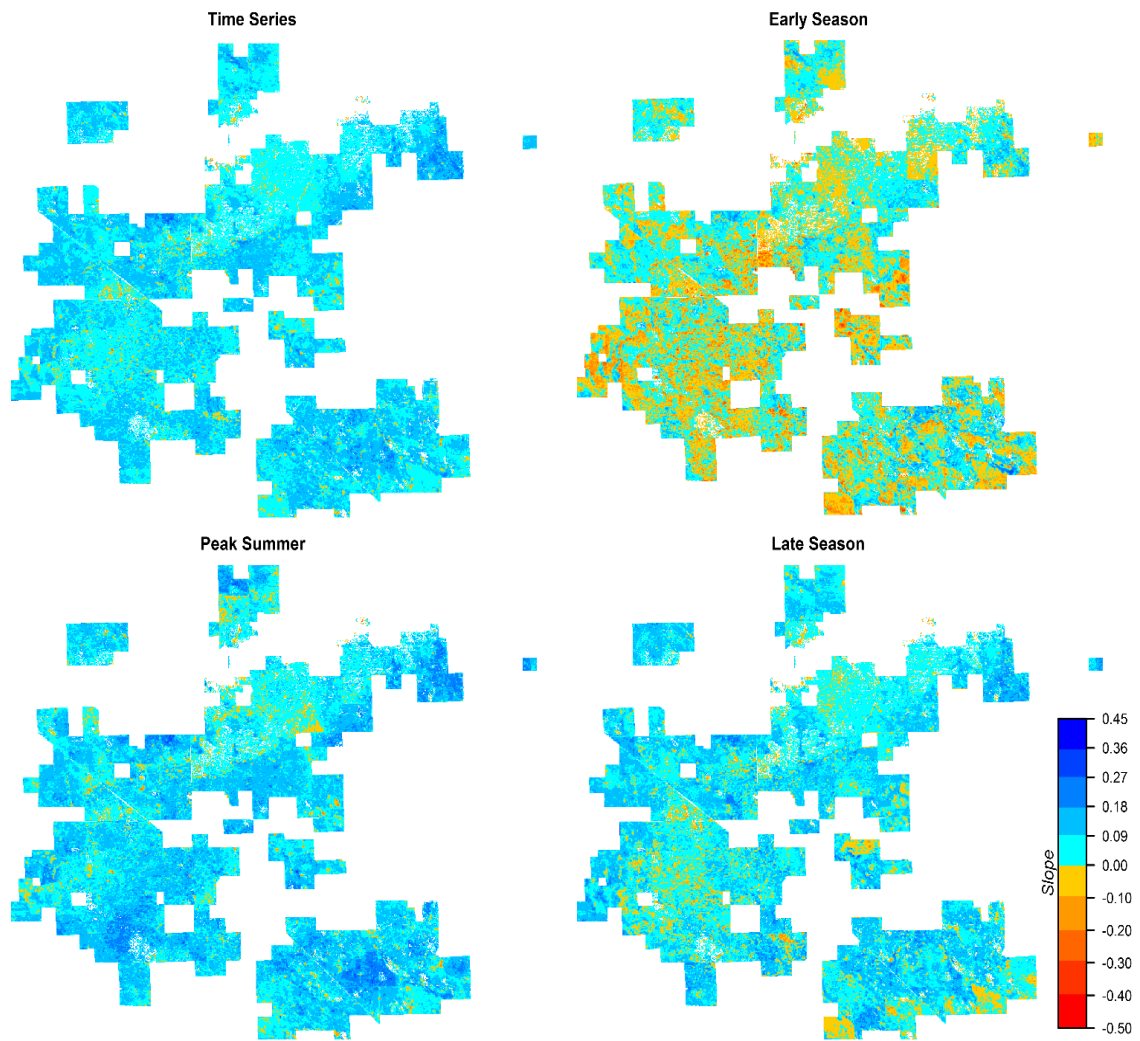


Figure 23. Running Days slopes for the NDVI through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.



Figure 24. Running Days slopes for the SWIR32 through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

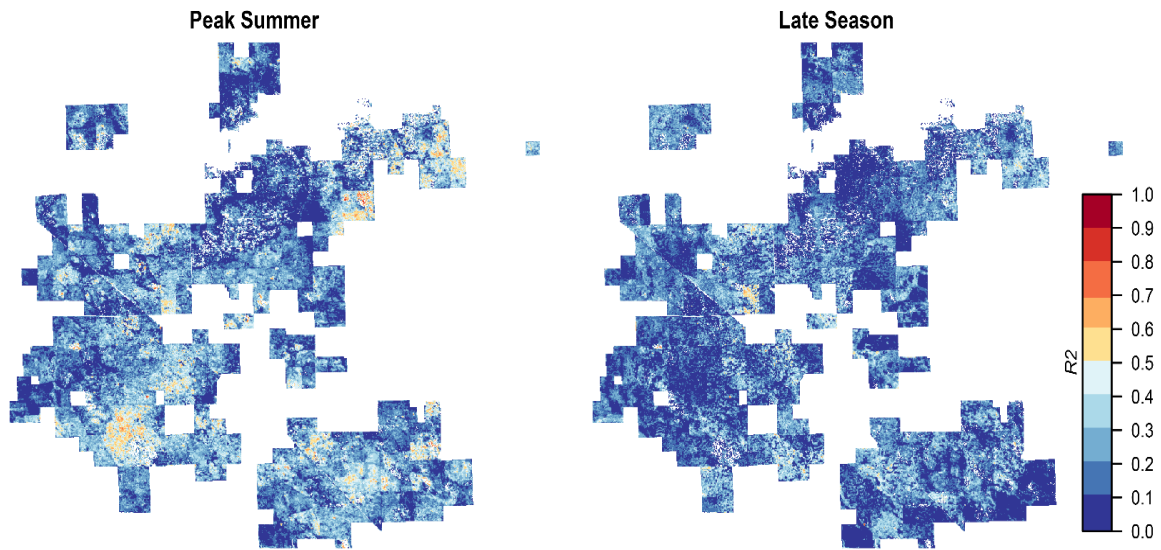


Figure 25. Running Days R^2 values for the CI through the Peak Summer and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

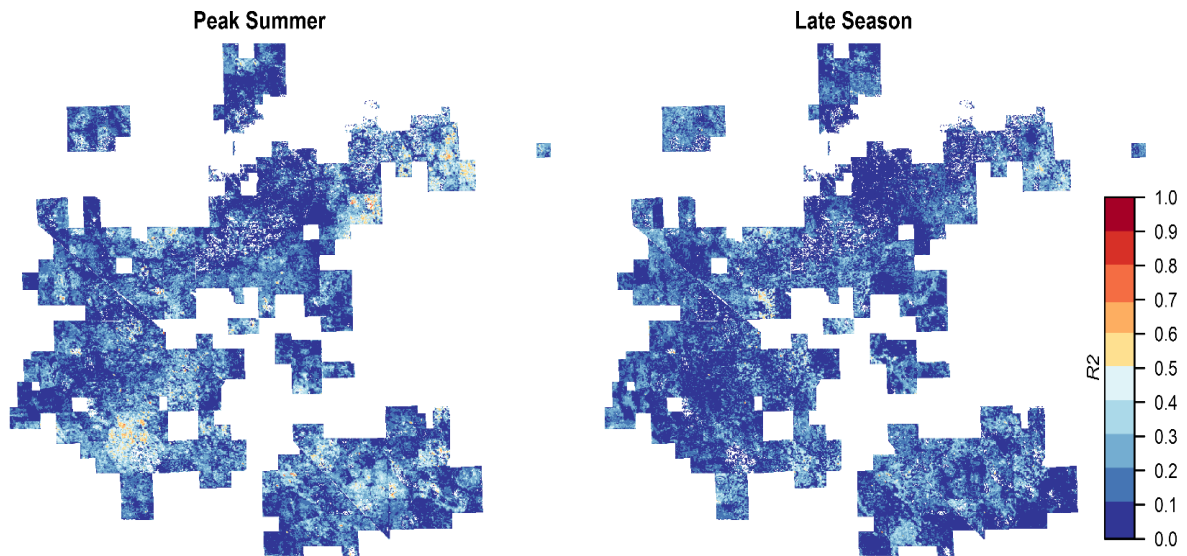


Figure 26. Running Days R^2 values for the NDVI through the Peak Summer and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

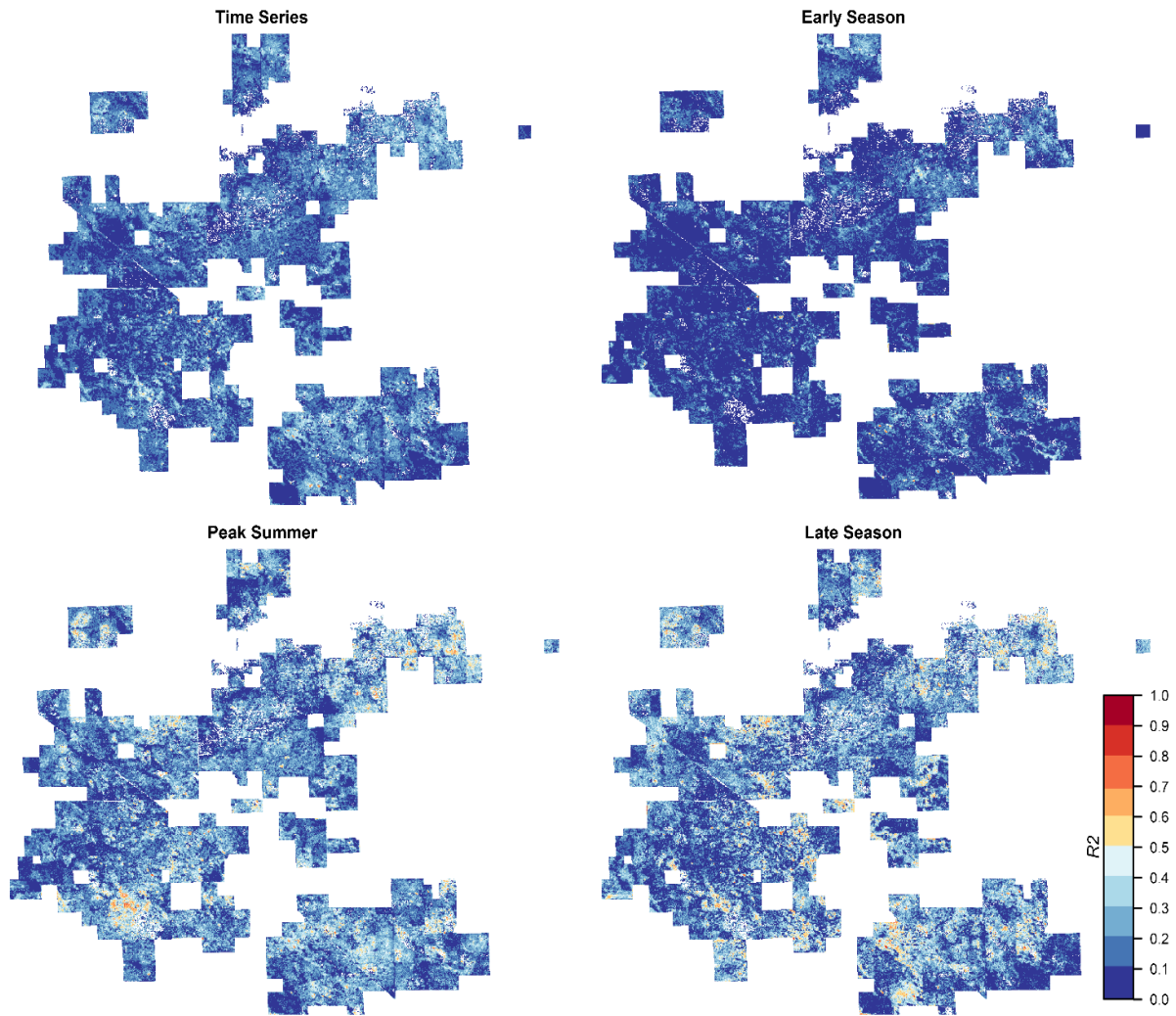


Figure 27. Running Days R^2 values for the SWIR32 through the Complete Time Series, Early Season, Peak summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

Box pots for the Running Days regressions for the CI (Figure 28) and NDVI (not shown) were very similar with the deltaic plain and hummock and swale having larger slopes than the sand dunes, particularly in the Peak Summer and Late Season. This same trend was true when comparing R² values by landform (not shown). By GAP class for both the CI (Figure 29) and NDVI (not shown) the WMTGP and wetlands had the smallest slopes in the Early Season and Late Season but large slopes in the Peak Summer. This is highlighted by examining temporal trajectories for slopes in the inset labeled ‘wetland’ in Figure 22. Overall, variation for all VI’s across GAP classes and landforms by both slope and R² values was small, and therefore only the CI is shown.

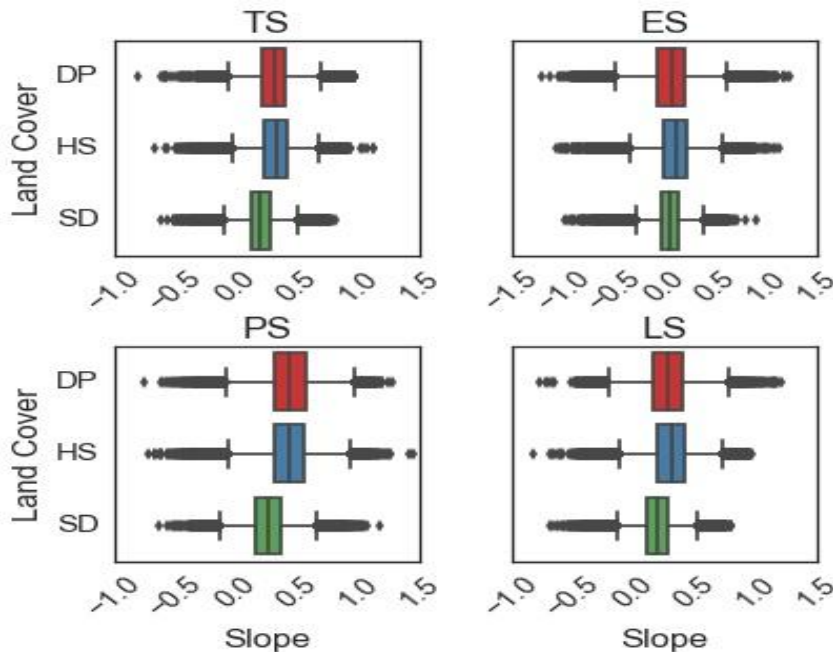


Figure 28. Boxplots of slopes by landform and for each of the four time segments for the CI. DP = Deltaic Plain; HS = Hummock and Swale and SD = Sand Dunes. TS = Time Series; ES = Early Season; PS = Peak Summer; LS = Late Season.

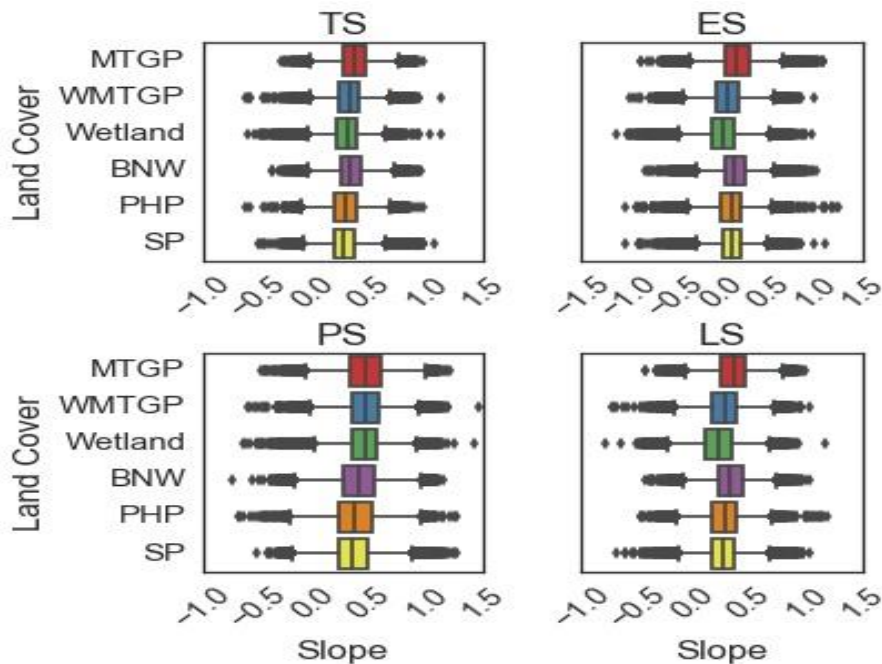


Figure 29. Boxplots of slopes by GAP class and for each of the four time segments for the CI. MTGP = Mesic Tallgrass Prairie; WMTGP = Wet Mesic Tallgrass Prairie; BNW = Bluestem-Needlestem-Wheatgrass; PHP = Planted Herbaceous Perennial; SP = Sand Prairie. TS = Time Series; ES = Early Season; PS = Peak Summer; LS = Late Season.

The Viking prairie which is ungrazed and is primarily native C_4 grass, the East Durler which is ungrazed and primarily C_4 grass and the West Durler which is invaded by Kentucky bluegrass and leafy spurge (C_3) were also compared to evaluate temporal differences in NDVI trajectories (Figure 30). Figure 22 highlights the location of these units. The Viking prairie has small NDVI slopes (mean of -0.05) in the Early Season, and so does the East Durler unit (mean -0.02). In contrast, the West Durler unit has larger NDVI slopes in the Early Season (0.06) (Figure 30). In the Peak Summer slopes increase on all three units, but more so on the Viking prairie (mean 0.15) and East Durler (mean 0.12) than the West Durler (0.10).

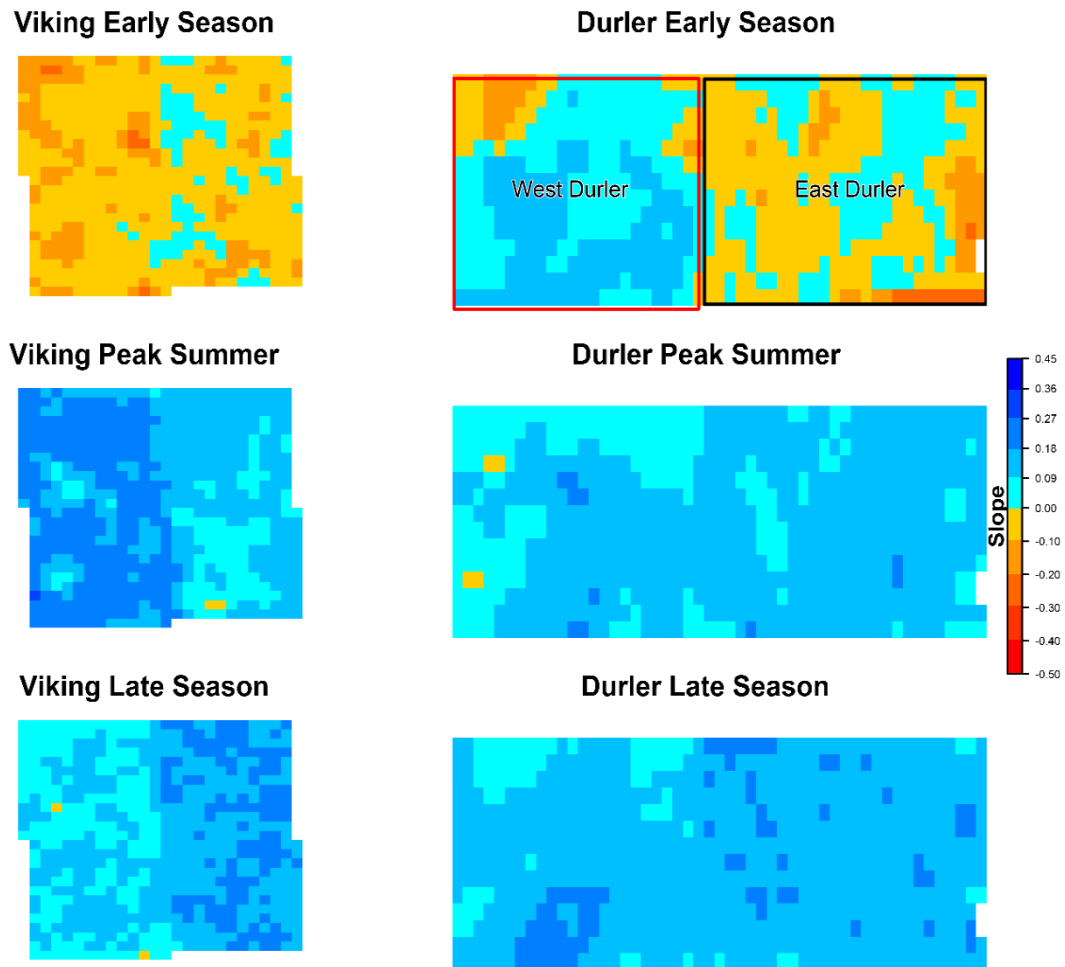


Figure 30. Comparison of NDVI slopes on the Viking prairie and Durler unit through the Early Season, Peak Summer and Late Season. The Viking Prairie is native C₄, West Durler is infested with *Poa Pratensis* while East Durler is native C₃ and C₄ grass.

While variation by GAP class and landform was small when compared with boxplots, there does appear to be differences in slopes in lowland locations (e.g. wetlands) and uplands when compared visually over the Early Season. Wetland locations have negative Running Days slopes in the Early Season while upland locations have positive slopes. By comparing locations with this variation in NDVI slopes to elevation and NAIP imagery it is apparent that lower elevations contain wetland communities, and have negative Running Days slopes for NDVI and upland locations have positive Running Days slopes for NDVI (Figure 31).

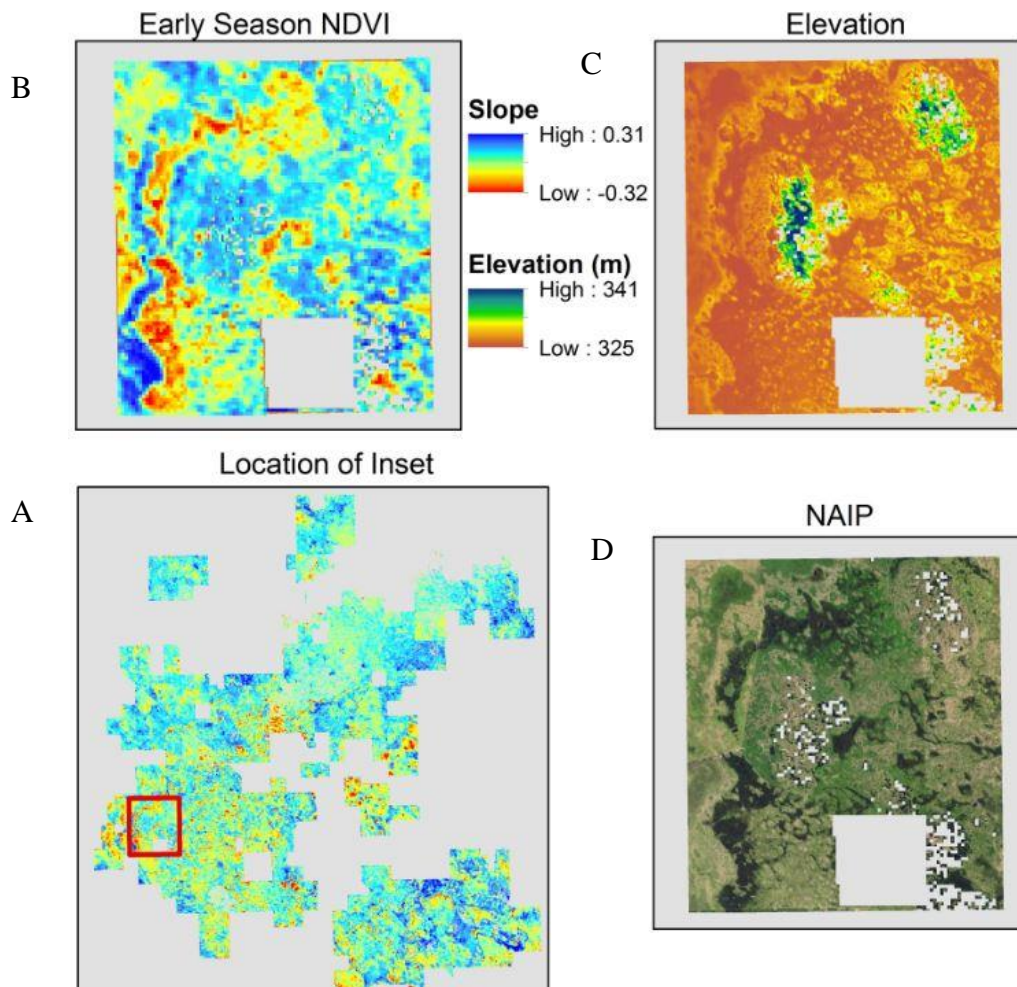


Figure 31. Location of inset (A) for comparison of Running Days NDVI slopes in the Early Season (B) on locations with lowlands which are associated with wetlands, and uplands with drier soils. Elevation from 1m Lidar (C) and true color NAIP imagery (D) are also shown.

Antecedent Precipitation regressions

Given the trends observed in VIs in the previous section, the next logical step was to explore the relationships between the VIs and APRCP as a major driver of vegetation dynamics. The regression results for APRCP are presented in the same format as the Running Days regression results, with per pixels regressions compared for the CI, NDVI and SWIR32 for pixels with the best R^2 values over the Complete Time Series shown first, and then maps which compare slopes and R^2 values for each of the three VI's are presented. When applicable, boxplots which detail variation in slopes and R^2 values by landform and GAP class are shown. In addition, a summary of the significance of regressions between APRCP and NDII is examined since it would be expected that NDII would be sensitive to trends in precipitation.

The scatter plots with the line of best fit for the pixel regressions between VIs and APRCP for the largest R^2 values through the Complete Time Series show relatively strong relationships for the CI, NDVI, and SWIR32 (Figure 32). Table 4 shows regression results for each pixel and VI from the scatter plots.

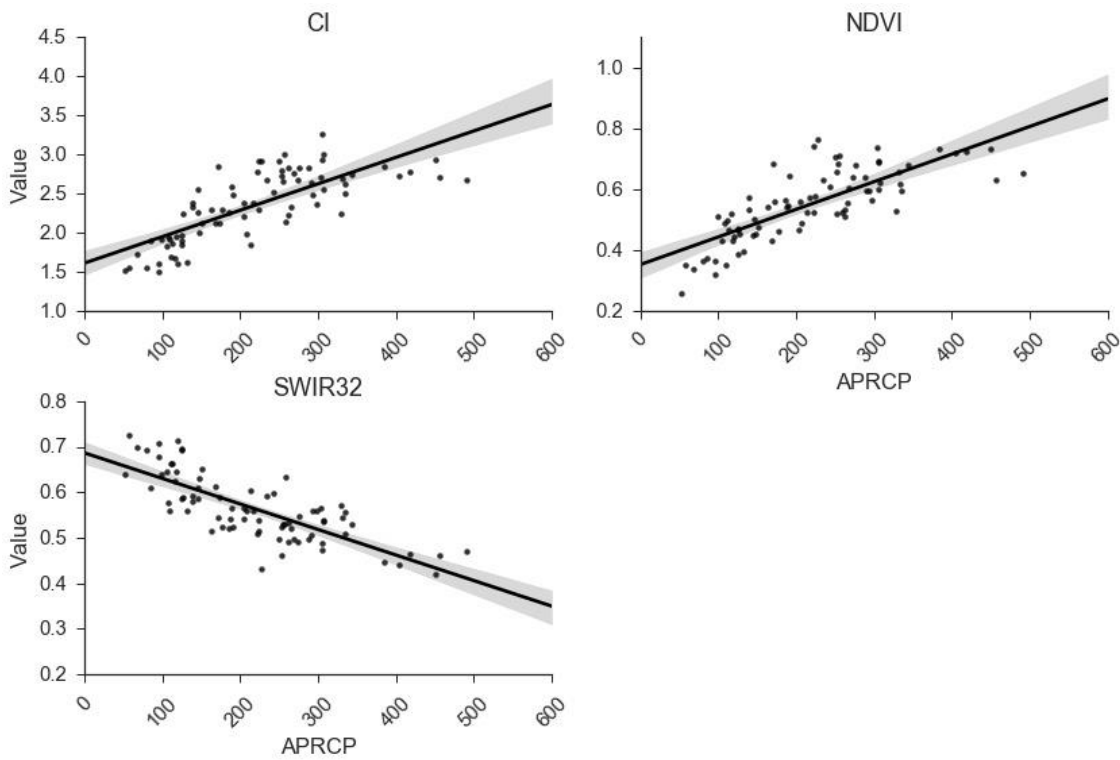


Figure 32. Scatter plots and lines of best fits for the pixel with the largest R^2 values through the complete time series the CI, NDVI and SWIR32.

Table 4. Regression results for each pixel and VI from the largest R^2 comparisons in Figure 32.

Index	R2	Slope	RMSE	p-value
CI	0.58	0.68	0.29	0
NDVI	0.6	0.18	0.07	0
SWIR32	0.6	-0.11	0.05	0

The spatial patterns of regression slope values and R^2 values for NDVI (not shown) were very similar to those for the CI (Figure 33, 34). Slopes and R^2 values were largest in the Early Season and smallest in the Peak Summer where numerous pixels with negative slopes are present. The same is true for SWIR32 except the direction of change in slopes is opposite (Figure 35, 36).

For the APRCP regressions differences in slopes by landforms are not shown as the results are the same as those for the Running Days regression, which is that for the CI and NDVI slopes were slightly larger on the deltaic plain and hummock and swale than on the sand dunes in the Complete Time Series, Early Season and Late Season. There was little variation in the Peak Summer. SWIR32 had very little variation in slope.

For the CI and NDVI there was little variation in R^2 by landform in the Peak Summer and Complete Time Series, but in the Early Season the deltaic plain had smaller values than the hummock and swale and sand dunes, and in the Late Season the sand dunes had smaller values than the deltaic plain and hummock and swale (not shown).

The CI (Figure 37) and NDVI (not shown) had similar trends in slopes across GAP classes, and there was little variation overall.

In summary, R^2 values for the regressions between APRCP and all VI's are largest in the Early Season and smallest in the Peak Summer. There is little variation in slope by landform or GAP class for any VI. Lastly, while NDII was not shown in this assessment, it is important to note that very few pixels are significant for NDII in the Peak Summer, and that in the Late Season only 31% of wetland and only 40% of WMTGP pixels are significant which is much less than for any other GAP class.

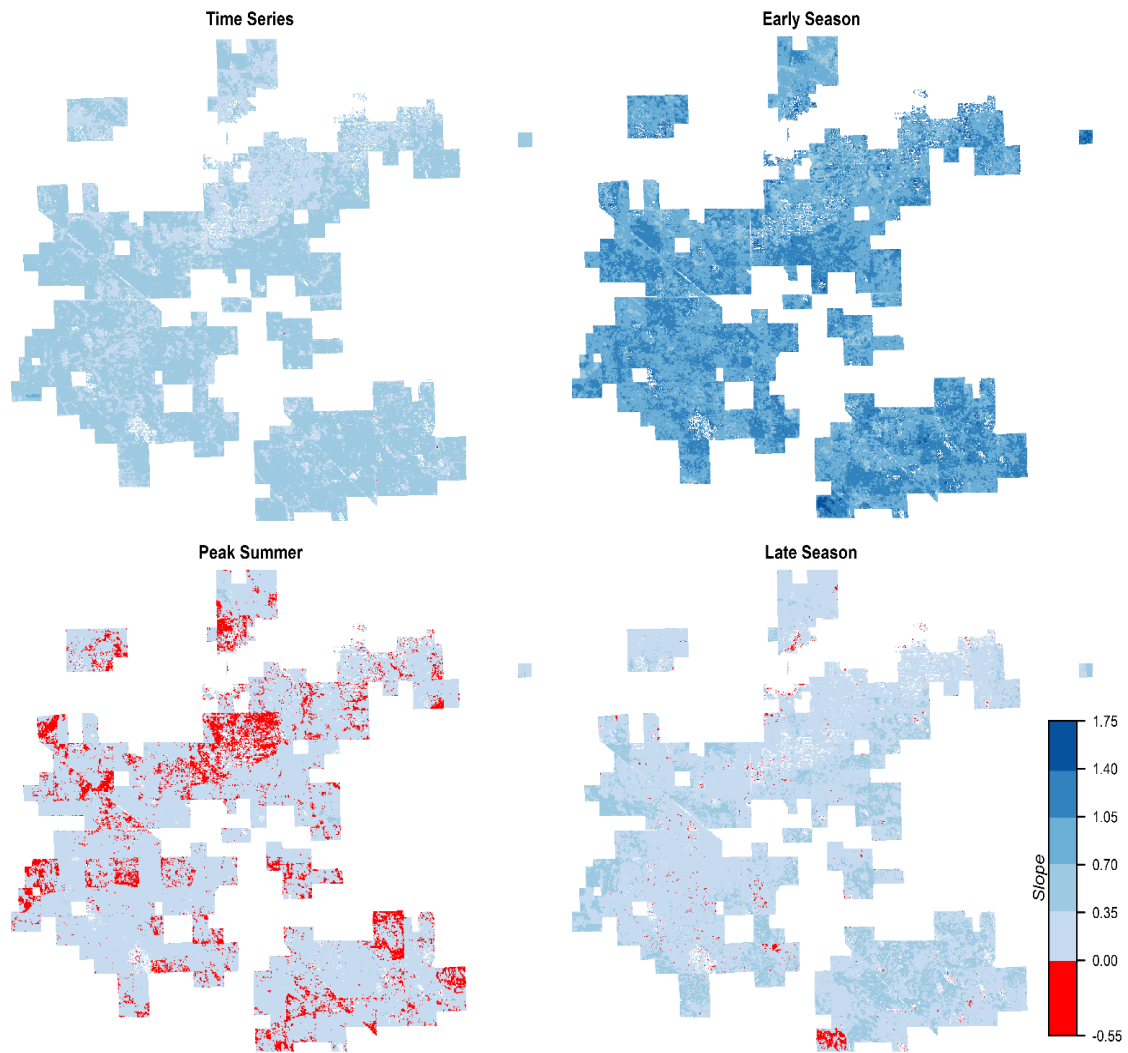


Figure 33. APRCP slopes for the CI through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

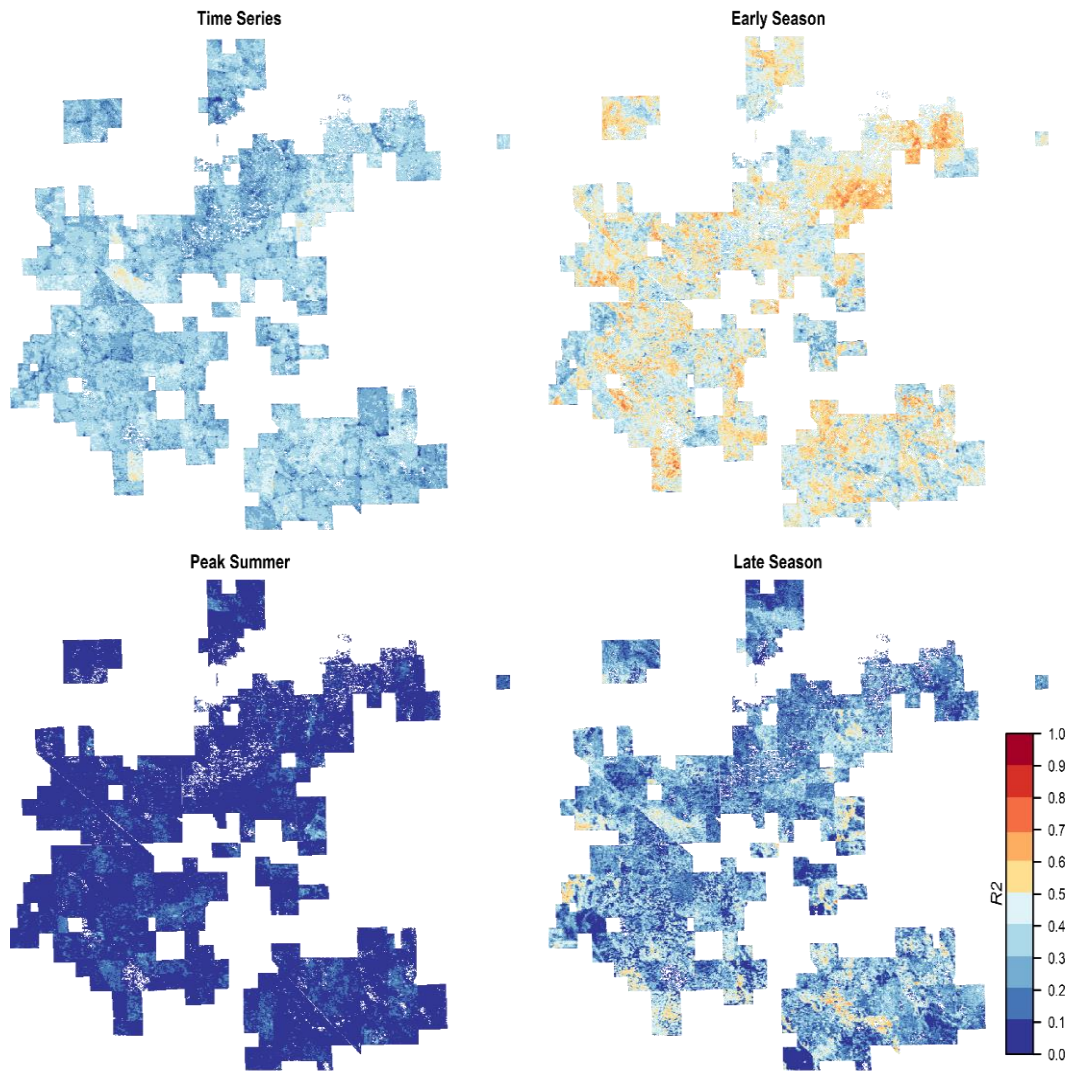


Figure 34. APRCP R² values for the CI through Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

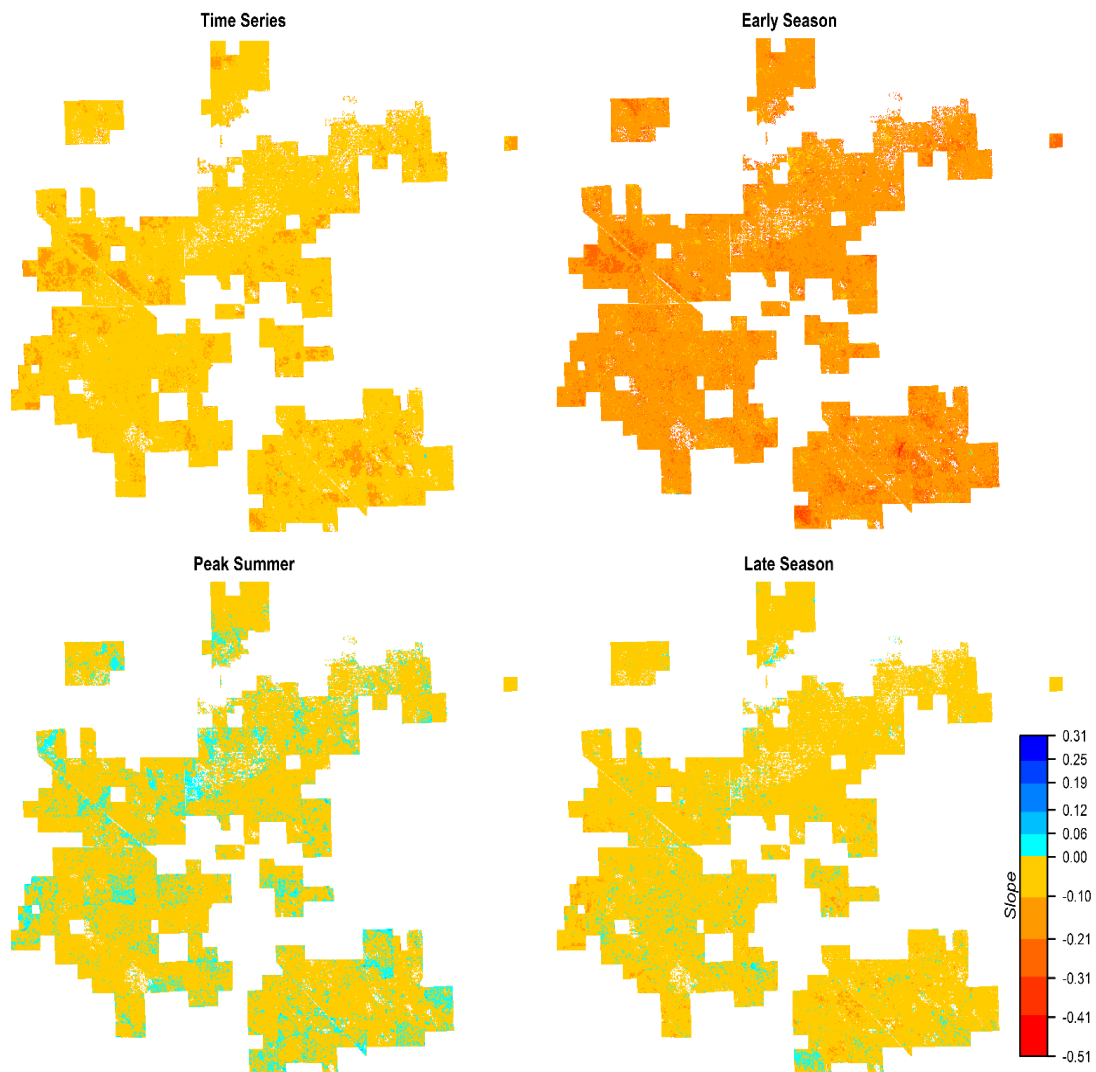


Figure 35. APRCP slopes for SWIR32 through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

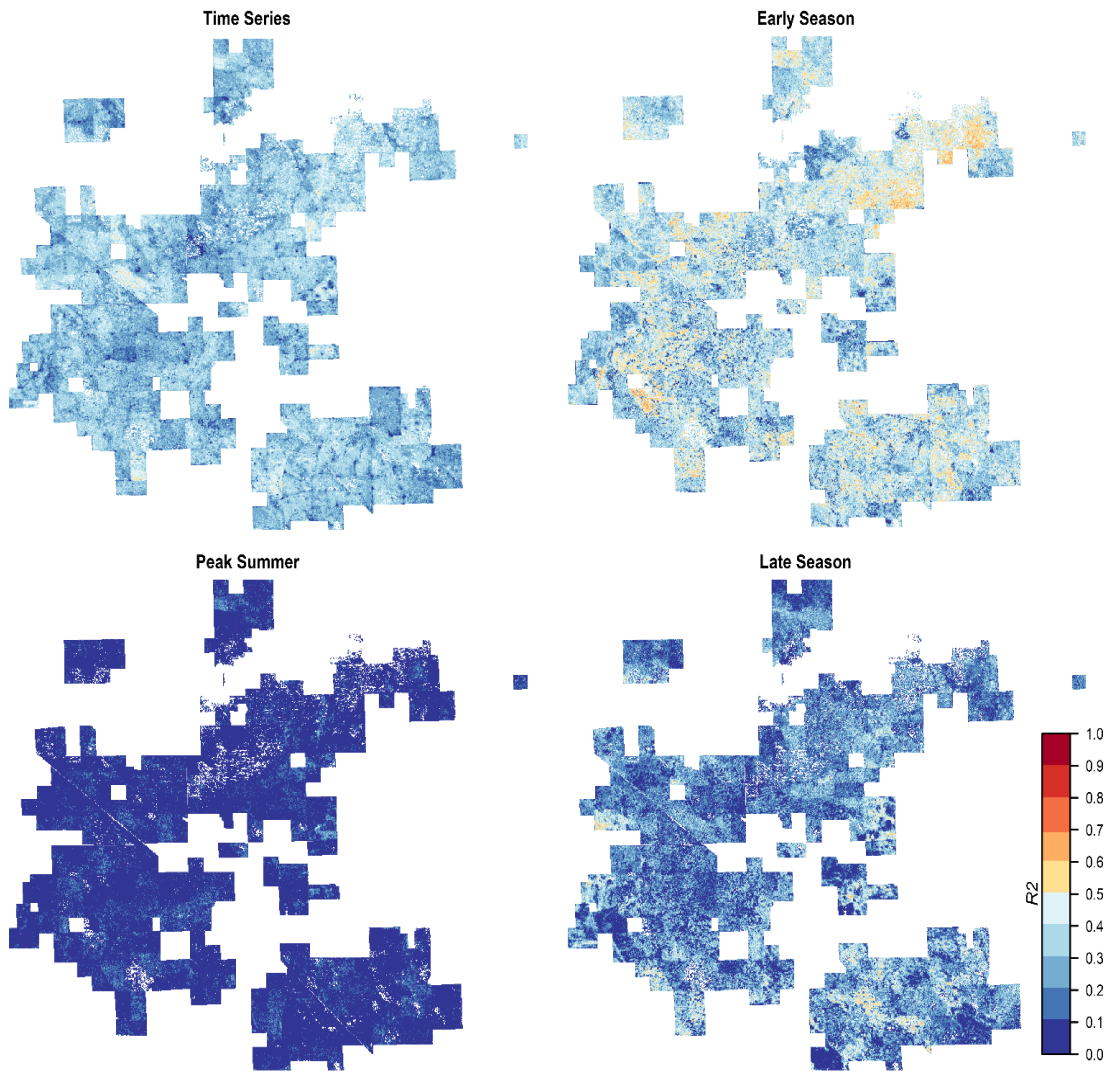


Figure 36. APRCP R² values for SWIR32 through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

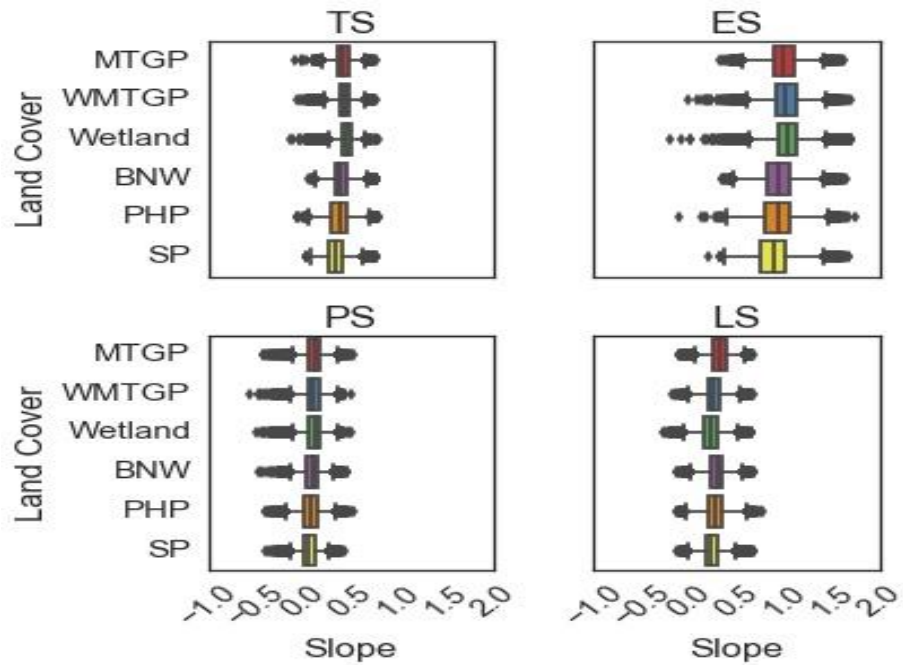


Figure 37. Boxplots of slopes by GAP class and for each of the four time segments for the CI. MTGP = Mesic Tallgrass Prairie; WMTGP = Wet Mesic Tallgrass Prairie; BNW = Bluestem-Needlestem-Wheatgrass; PHP = Planted Herbaceous Perennial; SP = Sand Prairie. TS = Time Series; ES = Early Season; PS = Peak Summer; LS = Late Season.

Antecedent growing degree days regression

Presentation of results of regression between AGDD and VIs follows the same as the previous sections. Scatter plots showing the regression line of best fit for the pixel with the largest R^2 values show more scatter in the point distribution than APRCP (Figure 38). This scatter suggests that AGDD may have less influence on the VI signals than APRCP. Table 5 shows regression results for each scatter plot.

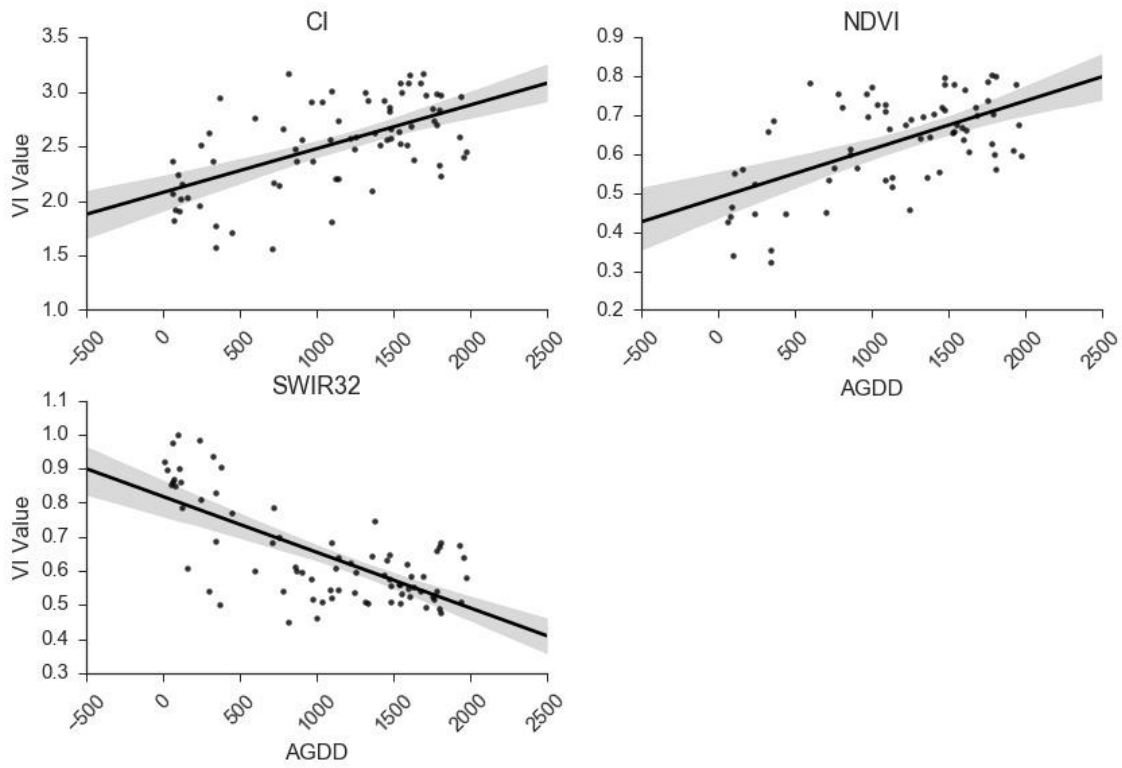


Figure 38. Scatter plots and lines of best fits for the pixel with the largest R^2 values through the complete time series the CI, NDVI and SWIR32.

Table 5. Regression results for each pixel and VI from the largest R^2 comparisons for the AGDD regressions in Figure 38.

Index	R²	Slope	RMSE	p-value
CI	0.34	0.2	0.33	0
NDVI	0.34	0.0.06	0.1	0
SWIR32	0.5	-0.08	0.1	0

Per pixel regression results comparing slope values and R^2 values for the CI (Figure 39, 41) and SWIR32 (Figure 40, 42) indicate that there is little variation in slopes between seasons for both VI's compared to the Running Days and APRCP results. There was little spatial or temporal variation in AGDD slopes for NDVI or SWIR32, although the amount of negative pixels increases from the Early Season to Late season for CI (positive pixels for SWIR32). R^2 values for the CI are largest in the Peak Summer and smallest in the Early Season while for SWIR32 they are small differences between seasons. The spatial pattern in R^2 values did show some evidence of association with underlying structure such as allotments or landforms.

Trends in slopes across landforms were the same as previous results. The deltaic plain and hummock and swale had larger slopes than the sand dunes for the CI, and smaller slopes for SWIR32 (not shown). R^2 values were also largest for both VI's on the deltaic plain and hummock and swale.

There was little variation in GAP class by season for any VI and therefore they are not shown.

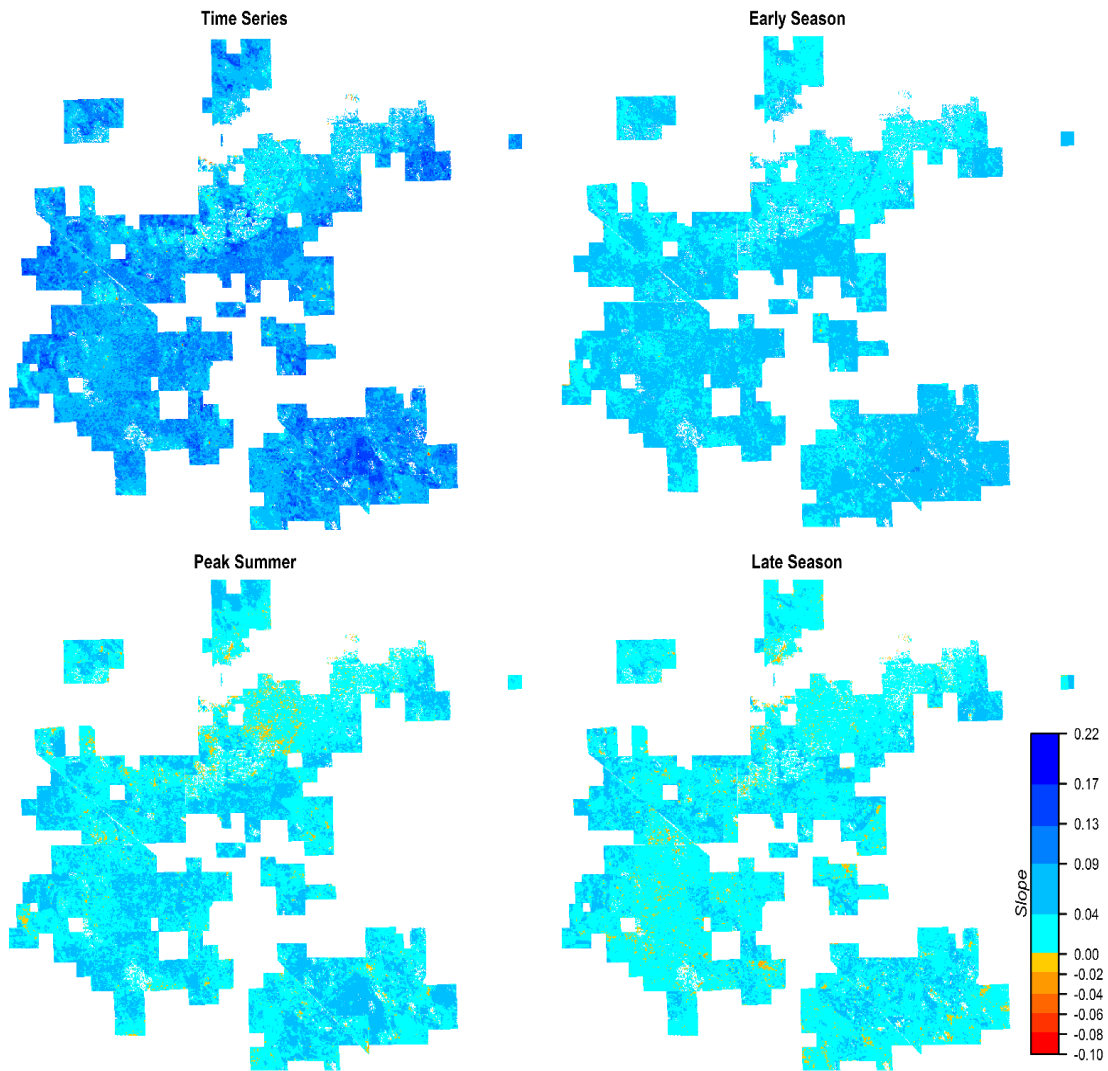


Figure 39. AGDD slopes for the CI through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

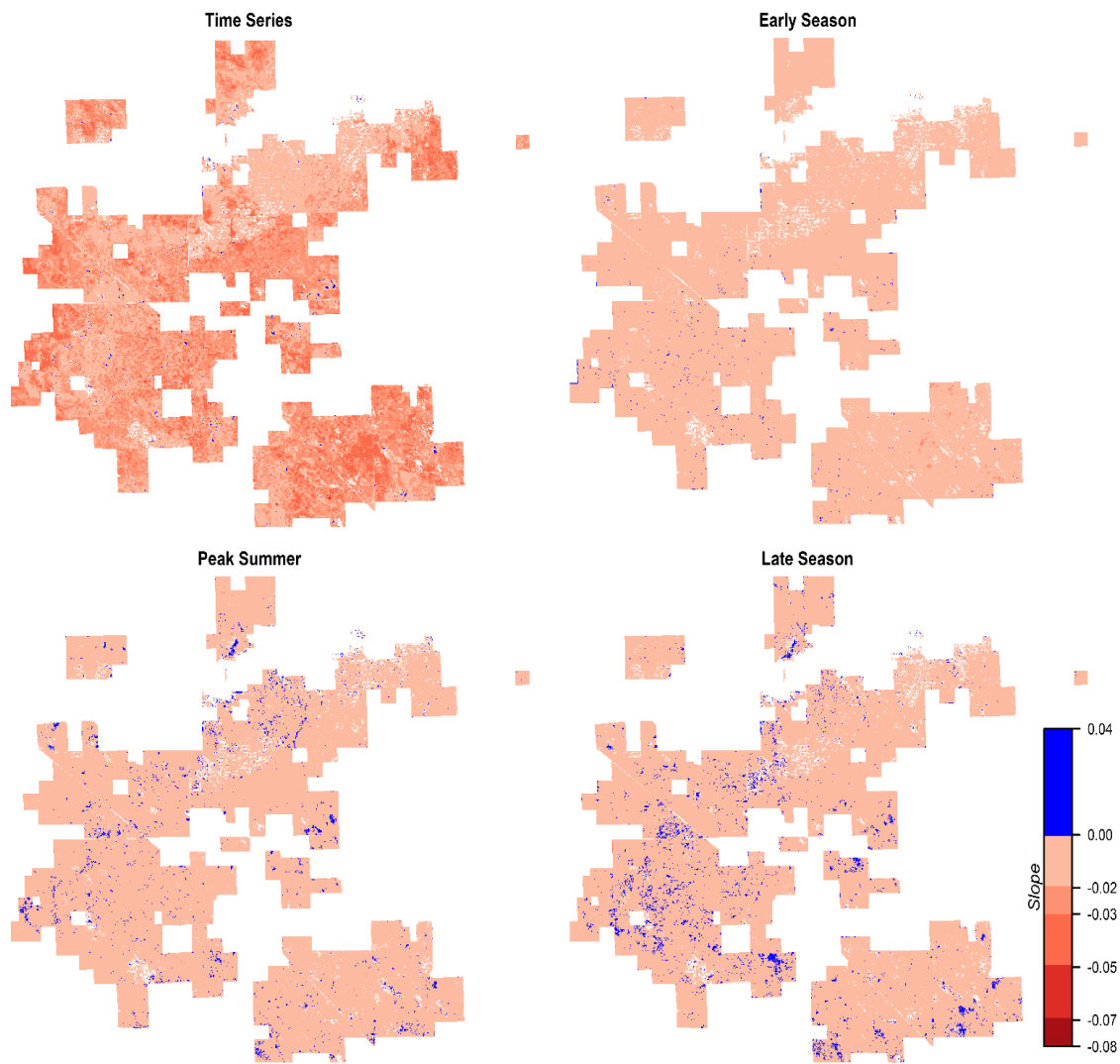


Figure 40. AGDD slopes for SWIR32 through Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

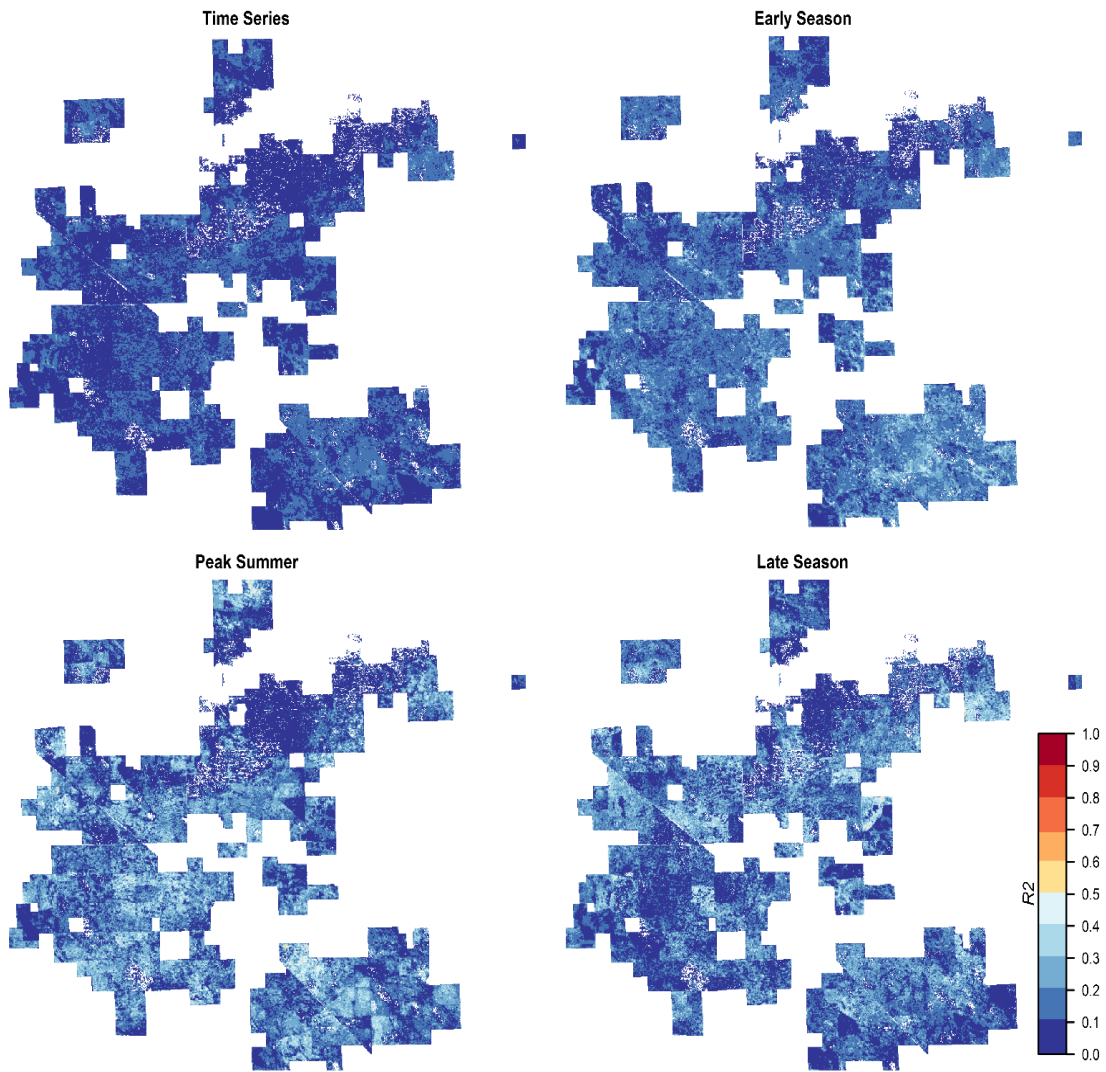


Figure 41. AGDD R^2 values for the CI through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

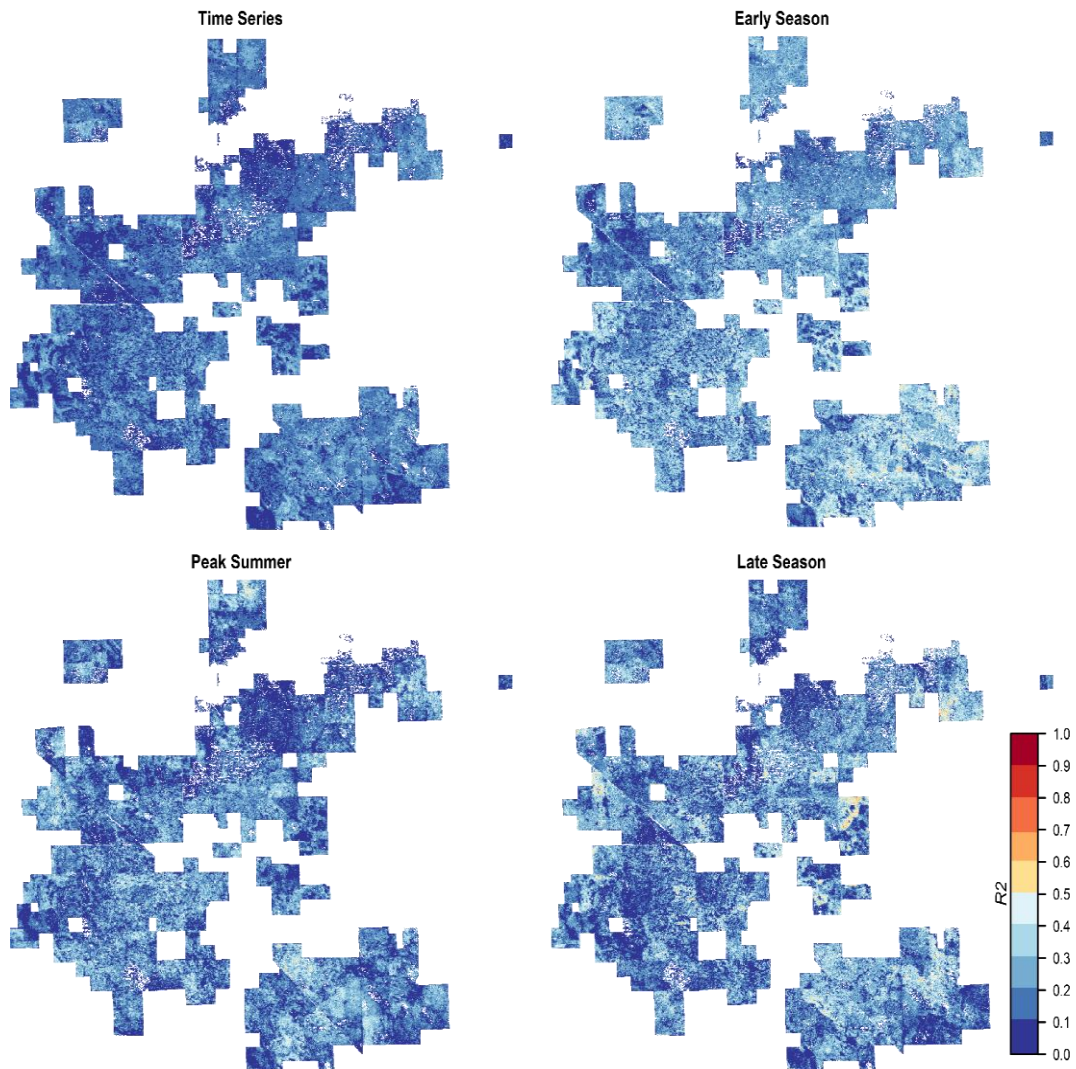


Figure 42. AGDD R^2 values for SWIR32 through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

Since AGDD should influence the behavior of major vegetation groups such as C_3 and C_4 grasses, the variation in R^2 values by GAP should be important, although there was little variation in R^2 values for the CI (Figure 43) or any of the other VI's.

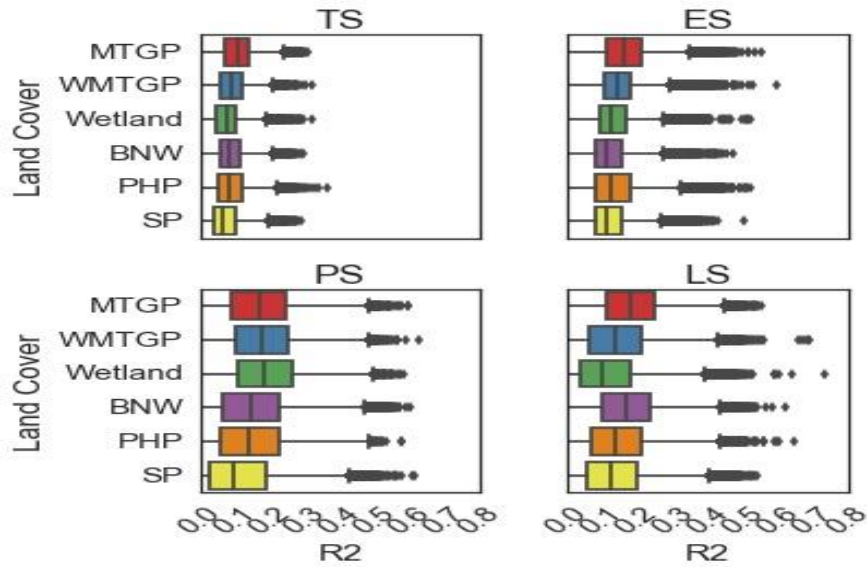


Figure 43. Boxplots of R^2 values by GAP class and for each of the four time segments for the CI. MTGP = Mesic Tallgrass Prairie; WMTGP = Wet Mesic Tallgrass Prairie; BNW = Bluestem-Needlestem-Wheatgrass; PHP = Planted Herbaceous Perennial; SP = Sand Prairie. TS = Time Series; ES = Early Season; PS = Peak Summer; LS = Late Season.

Additionally, while maps of NDII in relation to AGDD are not shown it is interesting to note that many locations had insignificant pixels – a pattern that did not occur for any other VI. A disproportionate number of these pixels are within the MTGP, WMTGP and wetland communities, particularly in the Early Season and Late Season (Table 6). In the Peak Summer BNW and SP have the fewest significant pixels.

Table 6. Percent of significant pixels per GAP community through the early season, peak summer, late season and complete time series for the NDII APRCP regressions. MTGP = Mesic Tallgrass Prairie; WMTGP = Wet Mesic Tallgrass Prairie; BNW = Bluestem-Needlestem-Wheatgrass; PHP = Planted Herbaceous Perennial; SP = Sand Prairie.

GAP Community	Percent Significant Early season	Percent Significant Peak Summer	Percent Significant Late Season	Percent Significant Complete Time Series
MTGP	46%	49%	23%	20%
WMTGP	46%	55%	23%	21%
Wetland	34%	60%	19%	23%
BNW	64%	36%	36%	33%
PHP	54%	51%	38%	37%
SP	76%	39%	56%	53%

Overall, R^2 values for the AGDD regression are largest in the Peak Summer and Late Season for all VI's except SWIR32, but there was little variation in slopes or R^2 values by GAP class. While NDII was not shown, it is interesting that the MTG, WMTGP and wetlands have the fewest significant pixels in the Early Season and Late Season, but that in the Peak Summer BNW and SP had the fewest significant pixels.

Grazing Regression

For the grazing regressions the CI will not be evaluated because the relationship between grazing pressure, VI response, and the functional properties of the vegetation were of interest. The CI represents not just one functional property of vegetation but multiple, and therefore separating which function is responsible for a change in the CI as a whole would be difficult. It is important to note that the Viking prairie is not assessed in the grazing analysis because there is no grazing present, and that allotment number 933 (Figure 2) is also not assessed because no historical records

were available. Grazing follows similar formats to previous regression results, with the exception that regression results from three distinct allotment with separate GAP coverages are compared.

The scatterplots showing the regression relationships for the largest R^2 values show that even the best relationships are highly variable with the NDVI and NDII showing a reasonable negative trend with grazing pressure, but high variability for SWIR32 and RGR (Figure 44). Since grazing is locally patchy, and these analyses are aggregated over many pixels in an allotment it is likely that variation will be much higher than for climate variables. Table 7 compares regression results for each VI for each pixel in the scatterplots.

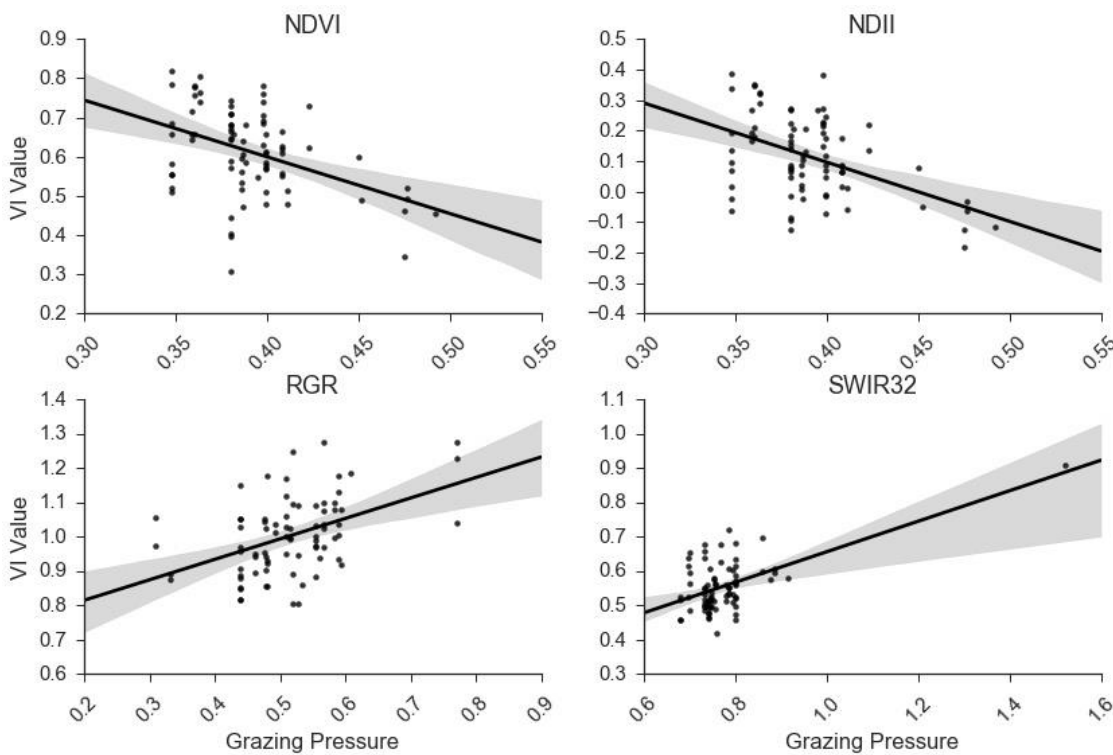


Figure 44. Scatter plots and lines of best fits for the pixel with the largest R^2 values through the complete time series the CI, NDVI, RGR and SWIR32.

Table 7. Regression results for each pixel and VI from the largest and smallest R² comparisons for the grazing regressions in Figure 44.

Index	Association	R2	Slope	RMSE	p-value
NDVI	Largest R2	0.18	-1.94	0.1	0
NDII	Largest R2	0.22	-1.94	0.12	0
RGR	Largest R2	0.2	0.10	0.1	0
SWIR32	Largest R2	0.34	0.44	0.06	0

Many areas had insignificant regression responses for relationships between grazing and NDVI both for the Early Season and Late Season. However, in the Peak Summer nearly all pixels are significant (Figure 45). NDVI grazing pressure primarily had a negative slope in the Early Season and Late Season in response to reduced grazing pressure, but in the Late Season positive slopes become more prevalent.

NDII (not shown) had few significant pixels in response to grazing except in the Peak Summer when slopes were primarily negative, but pixels that were significant in the Peak Summer had primarily positive slopes in the Late Season. RGR (not shown) and SWIR32 (Figure 46) had very similar spatiotemporal responses to grazing and the majority of pixels were significant for both. Temporally, RGR and SWIR32 had a mixed response in the Early Season with patches exhibiting both positive and negative slopes, in the Peak Summer slopes were mostly positive, and in the Late Season response was mostly negative.

R² values for NDVI (not shown), RGR (not shown) and SWIR32 (Figure 47) were also similar spatially and temporally. R² values were very small in the Early Season (0 – 0.1) but in the Peak Summer and Late Season many patches with values between 0.2 and 0.4 are present.

There was little variation by landform for slopes or R² values for any VI in relation to grazing pressure. There was also little variation in slope by GAP class for RGR (not shown) and SWIR32

(not shown) in the Early Season and Peak Summer, but in the Late Season the MTGP had smaller slopes than any other class. There was little variation in slopes by GAP class for NDVI (not shown).

Since the analysis showed spatial patterns in slope and R^2 that corresponded to allotment boundaries it was important to examine the results for allotments with particular responses. Allotments could be assigned to predominant association with species composition. Three allotments were chosen for close examination which represent mixes of different GAP classes, specifically, one allotment which has the highest percentage (in area) of BNW/SP, one which is has the highest percentage of WMTGP/wetland and one which has the highest percentage of MTGP.

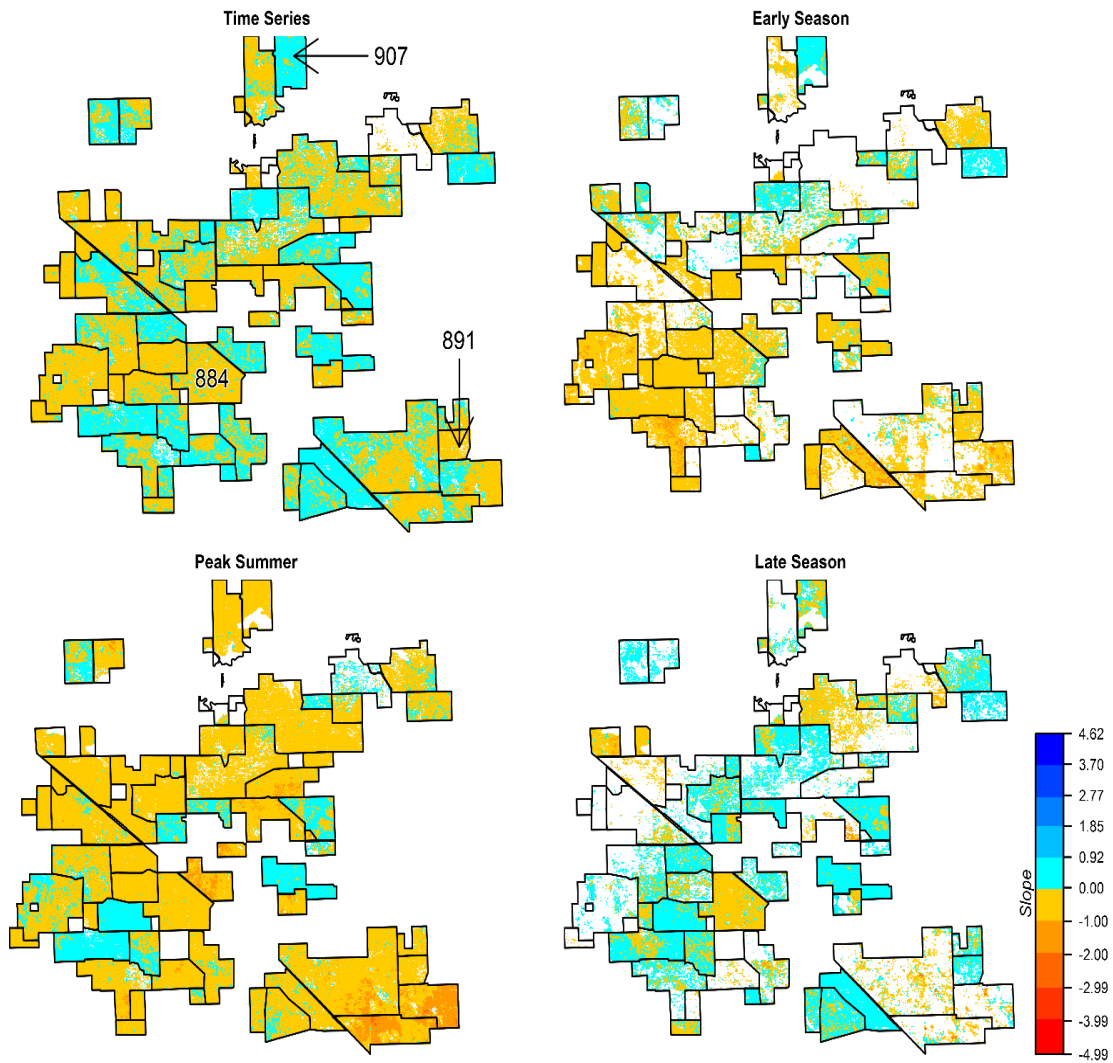


Figure 45. Grazing slopes for NDVI through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown. Numbers indicate three allotments which have variation in species composition.

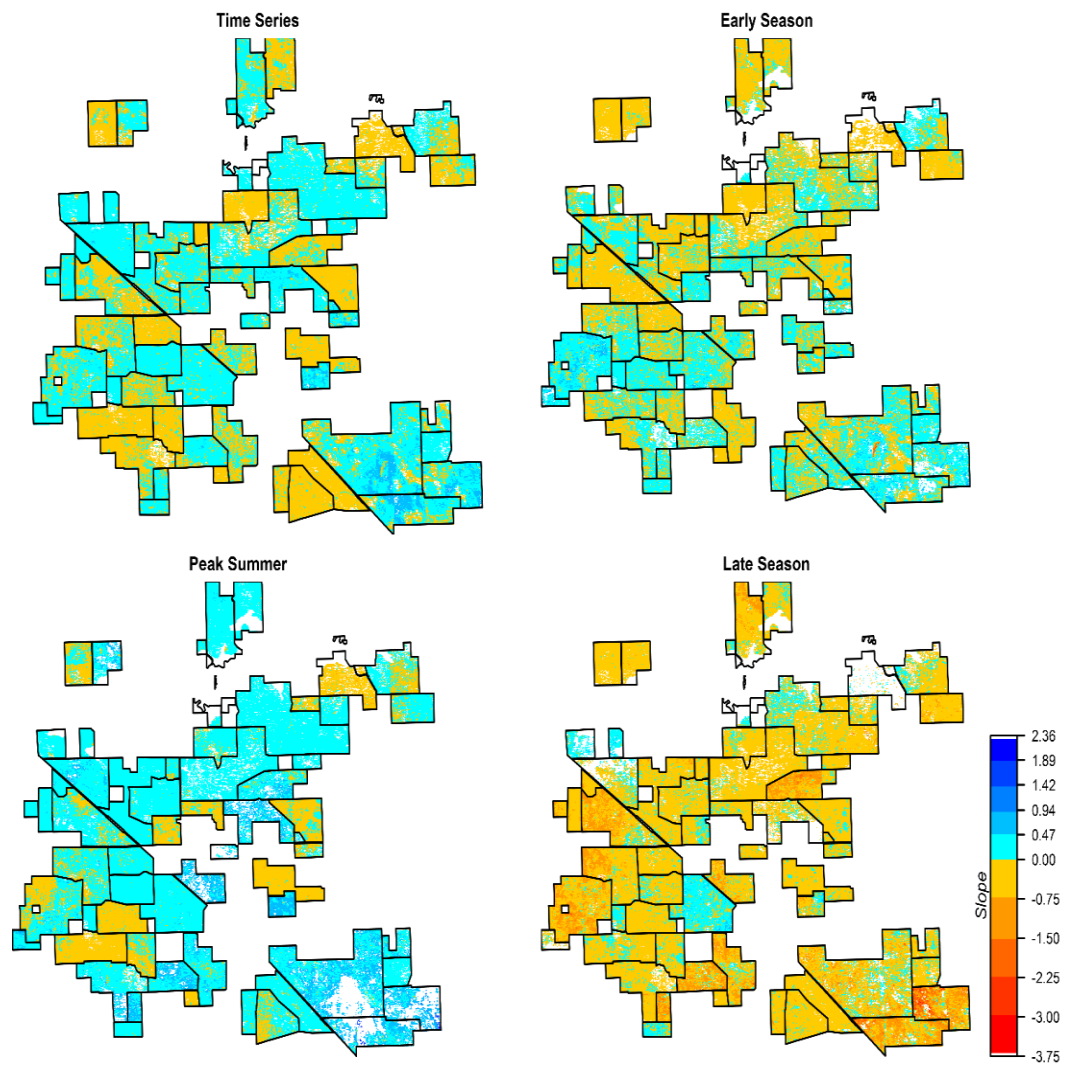


Figure 46. Grazing slopes for SWIR32 through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

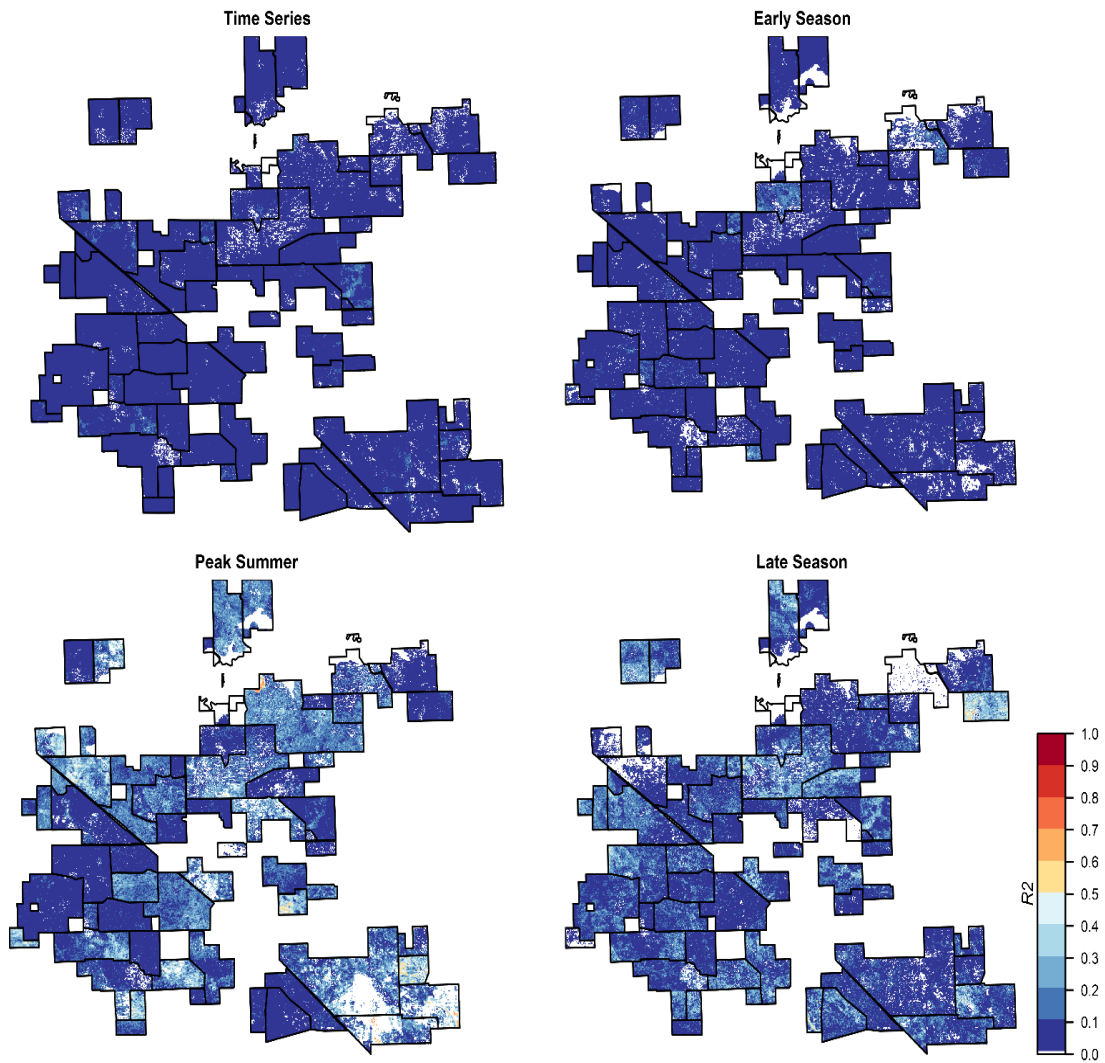


Figure 47. Grazing R^2 values for SWIR32 through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

Allotment 891 has the largest percentage of SP and BNW (83%), allotment 884 has the largest percentage of WMTGP/wetland (40%) and allotment 907 has the largest percentage of MTGP (43%). Refer to Figure 45 for allotment locations. NDII is not evaluated for this analysis as many pixels were non-significant.

In all three allotments there is separation in histograms of slopes (Figure 48) when comparing the Early Season and Late Season for the NDVI, RGR and SWIR32. For NDVI, except for in allotment 884, the Late Season always has a histogram of slopes which are shifted to the right

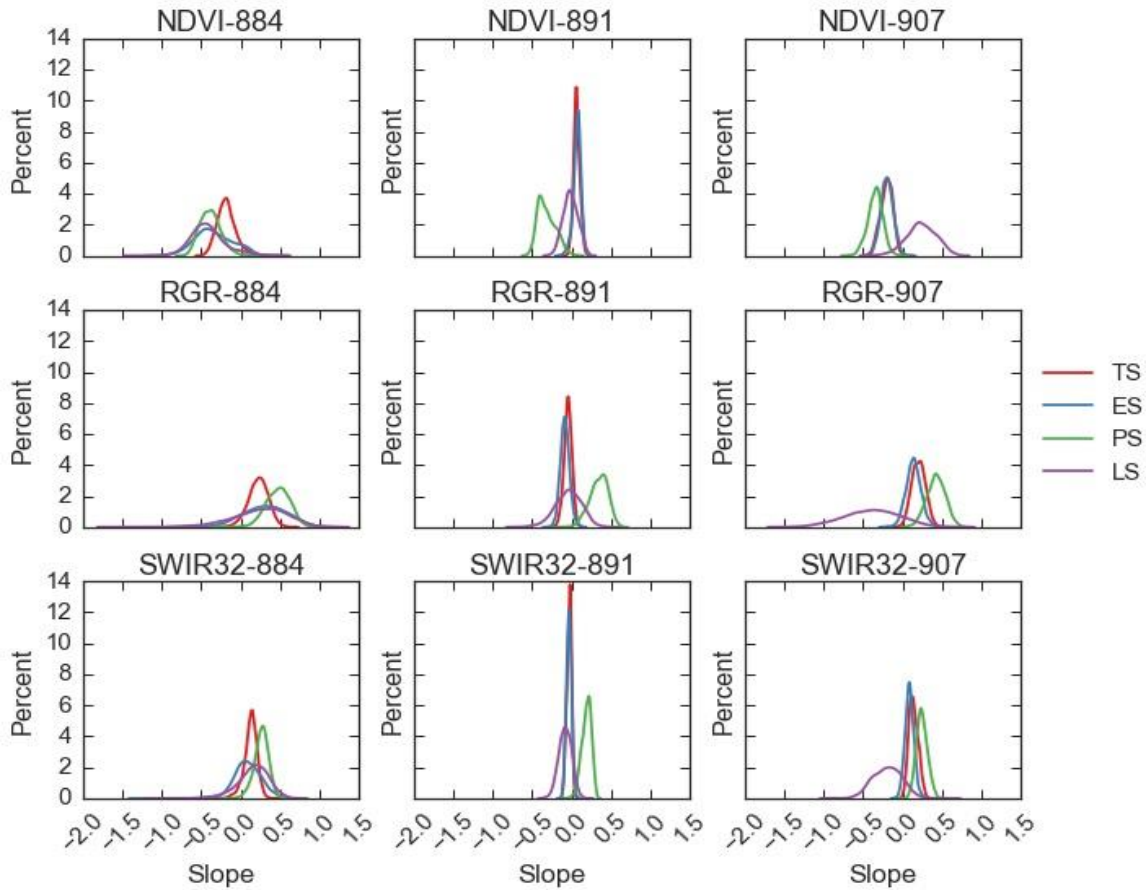


Figure 48. Histograms of slopes for NDVI, RGR and SWIR32 and for allotments 884, 891 and 907

(more positive) than the Early Season. The Late Season always exhibits a histogram of slopes shifted to the left (more negative) compared to the Early Season for RGR and SWIR32.

In summary, examining trends using simple regression is useful to evaluate how a single independent variable influences VI response, and how this response varies temporally. This simple regression analysis has shown that, in general, all VI's have changed the most for the Running Days regression in the Peak Summer, the most with APRCP in the Early Season and Late Season, the most with AGDD in the Peak Summer, and that all VI's have a variable response to grazing depending on the season. There is also variation in landforms and GAP classes, as the deltaic plain and hummock and swale have larger slopes and R^2 values than the sand dunes, regardless of independent variable, for the CI, NDVI and NDII. Slopes are more negative on the deltaic plain and hummock and swale for the RGR and SWIR32. By GAP class there is no consistent response when comparing classes and results are similar.

To evaluate how time, APRCP, AGDD, grazing and additional variables such as soil characteristics may be interacting to influence change in VIs with time multiple regression was implemented.

Multiple Regression

Presentation of multiple regression results is similar to that of simple regression, but with slight variation. Before results are shown on a per pixel basis variation in R^2 values per season and across all VI's is evaluated over all pixels on the SNG in one regression model. Maps of R^2 values on a per pixel basis for NDVI and SWIR32 are then shown followed by boxplots of slopes by landform and GAP class.

The methods section detailed how regressions were run sequentially to determine if R² values increased by adding more variables. Based on this analysis it was found that R² values increased minimally between sequence one to sequence two and three, and therefore only Running Days, APRCP, AGDD and grazing pressure are included in the following results for the multiple regression analysis.

The Early Season has the largest R² values across all VI's (Figure 49). The CI and NDVI have the largest R² while SWIR32 has the smallest. Except for the Peak Summer, where NDII has the largest R² value, the CI has the best model fits for all time segments. In the Early Season, Running Days, APRCP, AGDD and grazing pressure can explain about 45% of the variation for the CI values, but in the Peak Summer and Late Season the same variables only explain 20% and 18% of the variation respectively. Over the Complete Time Series these four independent variables explain

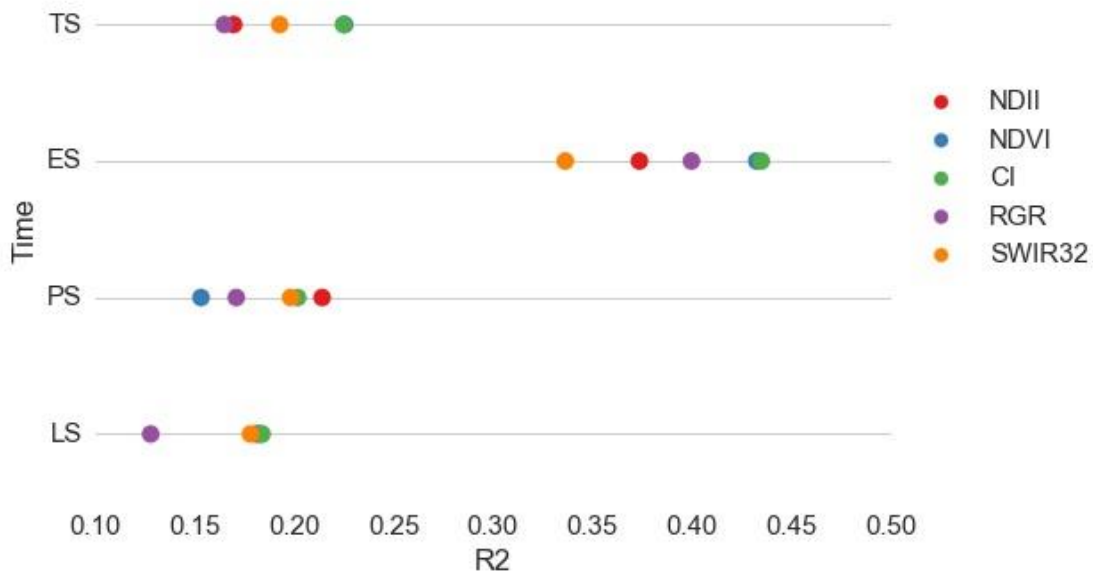


Figure 49. Comparison of multiple regression R² values by VI and time through all pixels on the SNG. All results are significant at $\alpha \leq 0.01$.

22% of the variation for the CI. RGR has low R^2 values compared to the other VI's in all seasons except the ES.

Spatial patterns of R^2 values for NDVI (Figure 50) and SWIR32 (Figure 51) are similar. In the Early Season R^2 values are slightly larger for NDVI, but for both VI's there are patches of R^2 values between 0.5 and 0.7. The Early Season has the largest R^2 values of any season for both NDVI and SWIR32. In the Peak Summer and Late Season patches of insignificant pixels are present, and R^2 values drop compared to the Early Season. Across landforms R^2 values for both NDVI and SWIR32 are largest on the deltaic plain and hummock and swale and smaller on the sand dunes. Across GAP class there is little variation for both VI's by class or season (Figure 52).

The combination of Running Days, APRCP, AGDD and grazing explain variation in VI values on SNG differently depending on season, and separate vegetative communities have variable response. However, these variables explained much more variation in multiple regression relationships in the Early Season when compared to the Complete Time Series and other seasons. While simple regression has provided insight into which independent variable drive this response, a random forest regression may offer further insight as feature importance for independent variables in relation to one another can be assessed.

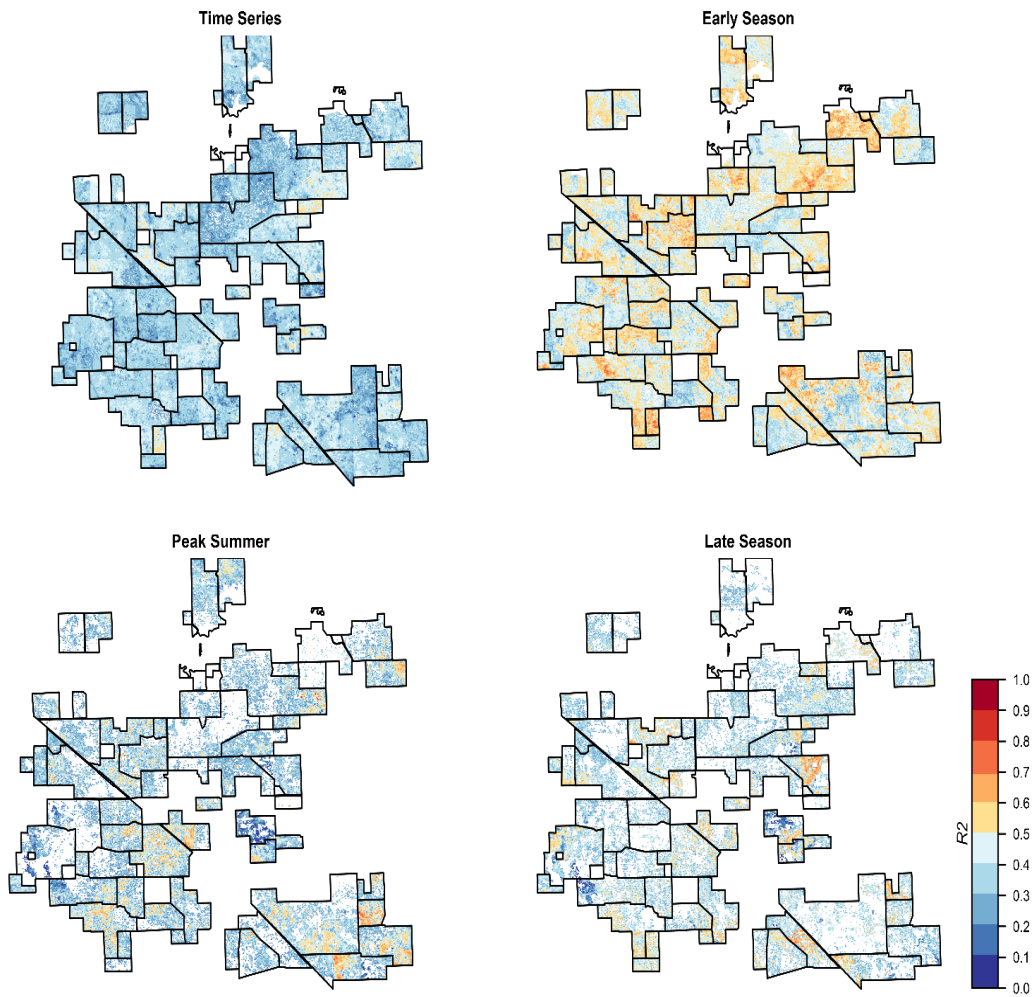


Figure 50. R² values for NDVI through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

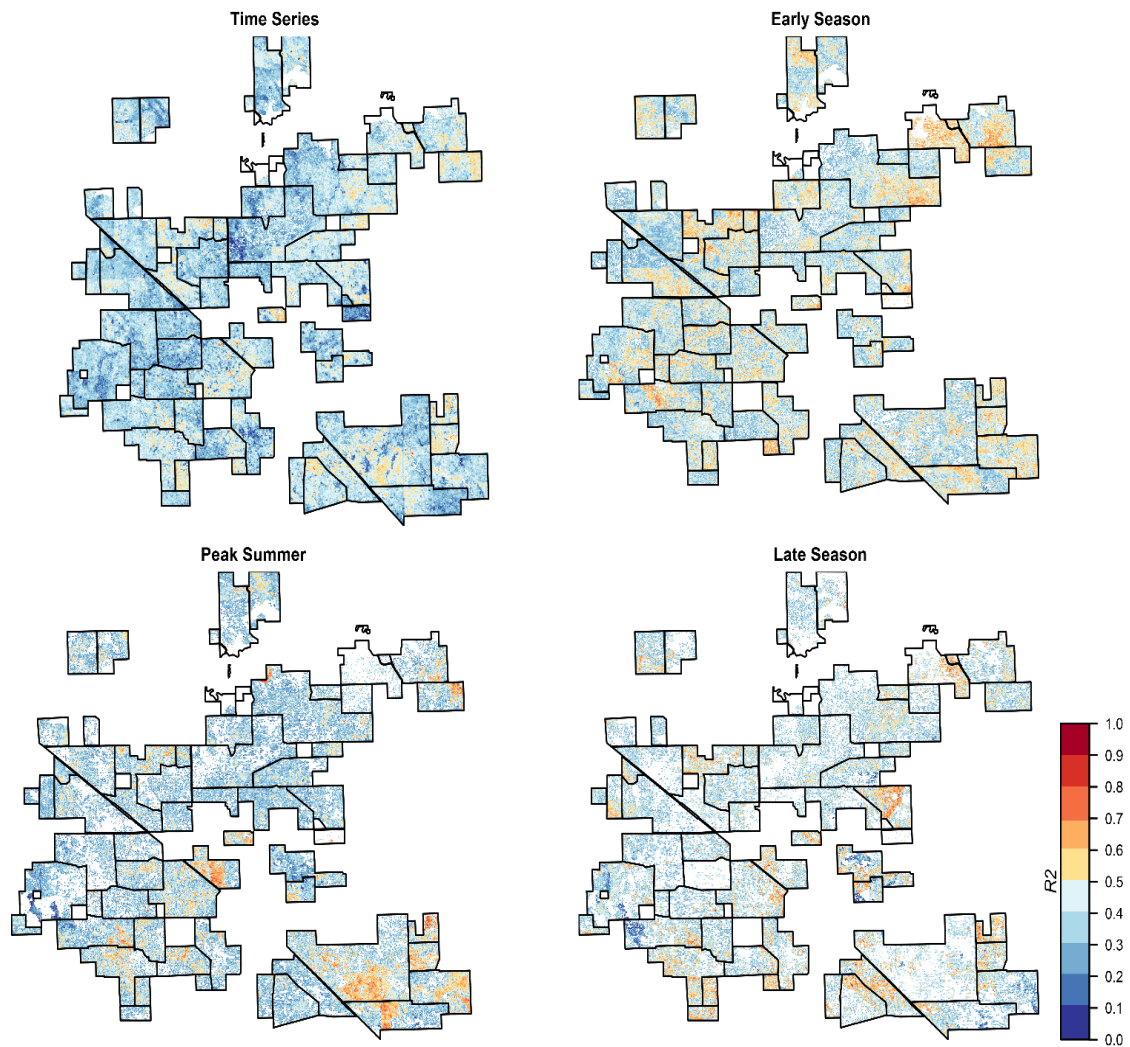


Figure 51. Adjusted R² values for SWIR32 through the Complete Time Series, Early Season, Peak Summer, and Late Season. Only significant pixels at $\alpha \leq 0.05$ are shown.

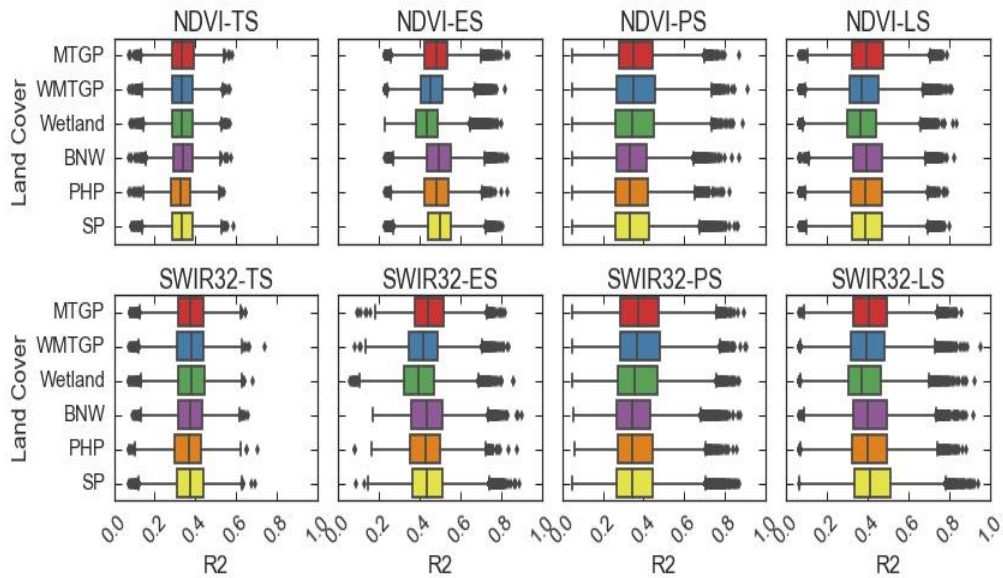


Figure 52. Boxplots of R^2 values by GAP class for the multiple regression results for both NDVI and SWIR32.

Random Forest Regression

To evaluate the importance of independent variables on VI values random forest regression was used. Feature importance with random forest regression should be associated with R^2 values for each VI from the simple linear regressions. For example, if APRCP has the largest R^2 values during the Early Season compared to all other independent variables, APRCP should also have the largest feature importance score in the Early Season for the random forest regression.

Random forest regression models were evaluated for each VI and for all four time segments just as they were for simple regression and multiple regression. Initially, random forest regressions were executed using all independent variables utilized in the third sequence of multiple regression which included APRCP, AGDD, grazing pressure, landforms, and soil characteristics. It was found that besides APRCP, AGDD, grazing pressure, AWS and SOC all other independent variables had very low feature importance and were thus excluded from the assessment.

Over the Complete Time Series, Early Season and Late Summer APRCP is the most important feature for all VI's except for SWIR32 (Figure 53). The most important feature for SWIR32 over the Complete Time Series and the Late Season is APRCP, but in the Early Season and Peak Summer AGDD is the most important. In the Peak Summer AGDD is the most important feature for all VI's. While APRCP and AGDD dominate the feature importance for all time segments, the importance of grazing and available soil water rise in the Peak Summer and Late Season for all VI's.

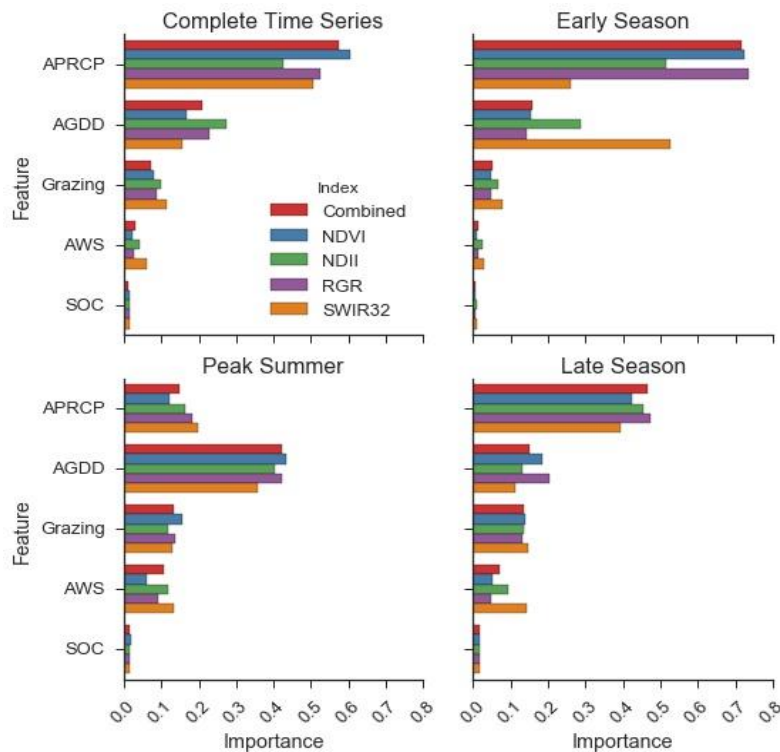


Figure 53. Feature importance for each VI for all pixels on the SNG through all four time segments. APRCP = antecedent precipitation; AGDD = antecedent growing degree days; AWS = Available Water

R² values in the training and test set indicate that the models generally perform best for the CI and NDVI and worst for SWIR32 (Table 8). In the Early Season R² values are large for all VI's, and drop slightly in the Peak Summer and Late Season. Differences between the training and testing set R² values are always small.

There should be associations with feature importance in the random forest regressions, and the R² values from simple regression and multiple regression. The multiple regression results showed that R² values were largest in the Early Season for both NDVI and SWIR32. The results for the simple linear regression also showed that NDVI and SWIR32 had the largest R² values in the Early Season in response to APRCP. The random forest results supports this for NDVI, but not for SWIR32. The random forest results show that AGDD is more important in the Early Season than APRCP for SWIR32, but the simple linear regression results show larger R² values in the Early Season in response to APRCP than AGDD. Still though, simple linear regression results showed that R² values were larger in the Early Season in response to AGDD for SWIR32 compared to NDVI.

R² values in the Peak Summer and Late Season were similar based on the multiple regression results, and the random forest indicates that AGDD is the most influential in the Peak Summer while APRCP is the most influential in the Early Season and Late Season. The simple linear regression results support this as both NDVI and SWIR32 have larger R² values in response to APRCP in the Early Season and Late Season than the Peak Summer. Although, the results from the random forest and multiple regression are generally in agreement, the random forest method provides a more robust assessment of the importance of the independent variables in determining the trend in VIs, and enables better discrimination of differences associated with vegetation types within allotments.

Table 8. Comparison of the training and testing set R^2 values for each Index across all time

Index	Time Segment	Train R^2	Test R^2
CI	Complete Time Series	0.70	0.67
CI	Early Season	0.85	0.84
CI	Peak Summer	0.64	0.63
CI	Late Season	0.67	0.65
NDVI	Complete Time Series	0.69	0.63
NDVI	Early Season	0.85	0.85
NDVI	Peak Summer	0.61	0.59
NDVI	Late Season	0.66	0.64
NDII	Complete Time Series	0.63	0.57
NDII	Early Season	0.79	0.78
NDII	Peak Summer	0.67	0.65
NDII	Late Season	0.67	0.65
RGR	Complete Time Series	0.60	0.53
RGR	Early Season	0.79	0.78
RGR	Peak Summer	0.59	0.57
RGR	Late Season	0.58	0.56
SWIR32	Complete Time Series	0.55	0.47
SWIR32	Early Season	0.72	0.70
SWIR32	Peak Summer	0.61	0.58
SWIR32	Late Season	0.58	0.56

CHAPTER V

DISCUSSION

The analysis of changes in VIs on the SNG based on linear regression over a 28 year time period from 1984 - 2011 showed that NDVI and NDII increased and RGR and SWIR32 decreased. Regression relationships also exhibited significant spatial variation in slope and coefficient of variation. The results suggest that both vegetation greenness (photosynthetic capacity) and landscape and vegetation moisture on the SNG have increased. When potential driving factors for these changes were explored in a random forest analysis, the most important factors by rank were antecedent precipitation (APRCP), growing degree days (AGDD), grazing pressure and available water storage (AWS). The analysis suggests a strong response to a shift in climate, and significant interaction between climate and grazing affecting the balance between C₃ invasive species and native C₄ tall grasses.

The VIs used in this study are functionally-related indicators of biochemical properties of the vegetation (Hill 2013). However, they are not equally amenable to interpretation in different landscapes. The NDVI is a proven indicator of photosynthetic capacity (Tucker 1979) and therefore the SNG has clearly become more photosynthetically capable over time, especially in the post-thaw spring period. The NDII is a proven indicator of moisture in vegetation (Hardisky and Smart 1983) since it roughly samples a major absorption feature, and the results show significant increases in NDII overtime as well. Hence, the SNG has become wetter over time.

However, the RGR is only a rough indicator of stress (Hill 2013) and generally behaved as a mirror of the NDVI. The SWIR32 is more difficult to interpret since it is best used in a two-way analysis with NDVI (Guerschman et al. 2009). It is sensitive to cellulose in dry vegetation though (Asner, Borghi, and Ojeda 2003), hence the increased greenness and wetness of SNG and reduction of vigor of C₄ grasses (discussed later) correlates with decreased values of SWIR32 over time. The composite indicator, CI, increased over time and acts as an overall aggregate response from the combined VI's. However, interpretation of this composite indicator is difficult since landscape sensitivity to the individual indices is highly unequal as indicated above, and it is not recommended that the approach used by this study to create a composite index is used.

If the GAP classification (Strong, Sklebar, and Kermes 2005) is considered an approximate, if not highly spatially explicit representation of the vegetation composition of SNG in the early 1990s, and the descriptive material on SNG from around 2010 (Svingen, Braun, and Gonzalez 2008) can be considered to be a reasonable general assessment of the vegetation composition around 15 years later, then some broad statements about the trends in composition can be made. Native tall grass species were more abundant/dominant on SNG at the time of the GAP classification but Kentucky blue grass and leafy spurge infestation has increased over recent decades (leafy spurge has been subject to controlled spraying and removal). The grazing pressure in allotments on SNG has varied over time but has generally remained high, and generally exceeds the recommended rates for these grasslands in ha/AU (Svingen, Braun, and Gonzalez 2008). In general, tall grass prairie and tall grass species are unsuited to set-stocking and continuous grazing. They evolved under migratory grazing by bison and periodic burning by natural grass fires. The common native C₃ mid grasses such as *Pascopyrum* spp, *Elymus* spp., *Heterostipa* spp. and *Koeleria* spp. are more tolerant of grazing than tall grass species such as *Andropogon gerardii*, *Sorghastrum nutans* and *Panicum*

virgatum. However, these grasslands were already contaminated with exotic cool season C₃ grasses such as Kentucky bluegrass (*Poa pratense*) and smooth brome grass (*Bromus inermis*), along with the persistent weed leafy spurge (*Euphorbia esula*).

In particular, Kentucky bluegrass is a mesic, sod-forming, grazing-tolerant species. It is active early in the growing season at post-thaw low temperatures, and thrives where water tables are high and moisture is seldom limiting. The increased precipitation trend on SNG combined with continuous set-stocking over the growing season provides an ideal environment to favor ingress and spread of Kentucky bluegrass. The set stocking suppresses growth and crown development in native tall grasses that don't become active until soil temperatures exceed 8-10 °C, and frosts are absent, and rely on peak summer temperatures for optimum growth and subsequent reproductive and over-wintering crown development.

The contrasting trends in VIs by season observed here support the above scenario for change in vegetation composition. There are several major points:

- a) The strong trend in NDVI with increased grazing pressure in the Early Season supports the increase in C₃ plant abundance from both native grasses and invasive species.
- b) The negative trend in NDVI with increased grazing pressure in the Late Season supports the reduction in vigor of the native tall grasses, and is consistent with higher cover of native and invasive C₃ species which have already become reproductive and ceased growth.
- c) The increased precipitation makes the SNG environment more suitable for all mesic species, but the grazing regime advantages the C₃ grasses and weeds, and disadvantages the C₄ tall grasses meaning they gain relatively less benefit from the additional soil moisture.

If it is accepted from this analysis that the changes to SNG detected by VIs are based on a combination of increased wetness and shifts in species composition away from C₄ dominance and towards C₃ invasive species, then there are important implications for ecosystem function associated with changes in photosynthetic potential, carbon storage, landscape water content, bare ground, and biomass (Hill et al. 2013). For instance, an increase in NDVI is likely to alter carbon storage dynamics as NDVI is closely associated with biomass and leaf area index (LAI), and increases in both NDVI and NDII is likely to alter moisture fluxes. Carbon has been found to be nearly-linearly related to carbon assimilation and transpiration on the Konza tallgrass prairie in Kansas (Hall and Scurlock 1991). While field measurements would be needed to confirm this finding on the SNG, it is likely that the association between NDVI, carbon assimilation and transpiration is similar on the SNG due to similarities in species composition. Numerous studies have evaluated the positive association of NDVI with LAI, which is a key variable related to biomass production, biochemical processes and water and carbon exchange, all of which are important characteristics in global change models (Asner, Scurlock, and Hicke 2003; Glenn et al. 2008; Fan et al. 2009).

Since so many of the C₃ species on the SNG are considered invasive, it would be useful for land managers to be able to detect when C₃ species invade locations which have historically been C₄ dominant. This analysis showed that there are large differences in trajectories of areas dominated by separate relative abundances of C₃ and C₄ plants. The Viking prairie and East Durler units, with many C₄ species, had negative mean NDVI slopes in the Early Season, but in the Peak Summer slopes were primarily positive. In contrast, the West Durler unit, heavily infested with

invasive C₃'s Kentucky bluegrass and leafy spurge, had positive slopes in the Early Season and Peak Summer, but the increase in slope values between the two seasons was not as large as the Viking prairie or East Durler. Therefore, further monitoring of locations which experience a transition of negative to positive slopes, particularly in the Early Season, may help identify if transitions between C₃ and C₄ communities are occurring. For example, if the Viking prairie begins to transition to larger NDVI values in the Early Season, it is likely that C₃ plants have begun to invade and management may better consider their actions.

It is also possible that lowland elevations, which consist of wetland communities, and upland communities which consist of plants adapted to more xeric soils have experienced different NDVI trajectories through time, specifically in the Early Season.

Lowland locations primarily have negative Running Days slopes for NDVI while upland locations primarily have positive slopes. Spring precipitation in southeastern North Dakota has increased in the past century (Karl and Knight 1998), and this increase could be suppressing vegetation in lowland areas by saturating plant roots. In upland areas, with lower water holding capacity, addition soil water from increased precipitation could be occurring which should result in an increased NDVI. Therefore, micro-topographic gradients on the SNG may be highly influential in determining trajectories of specific VI's.

Uncertainty and Future Research

One of the largest difficulties in any time series analysis with remote sensing data is the lack of available ancillary data to validate findings which are often needed at a yearly scale over long periods of time (Cohen, Yang, and Kennedy 2010; J. E. Vogelmann et al. 2016). This study is no different as there is only one source of information indicating what the vegetation composition was on the ground – the mid 1990's GAP survey. This is particularly problematic for studies attempting to identify gradual ecosystem change as more labor intensive data regarding spatial density of plants, plant vigor/health and soil moisture availability is needed over fine temporal scales (J. E. Vogelmann et al. 2016). Due to this lack of ancillary data, comparisons of median slopes and R^2 values by GAP classes may be misleading as it is not ensured a specific pixel has remained the same vegetative composition through time. Additionally, there is the possibility that a GAP class was misclassified in the survey itself. For example, the East Durler unit which should be classified as MTGP has a large portion classified as PHP, and therefore any evaluation of trends for certain pixels that should be considered MTGP are reflected in trends evaluating PHP which is incorrect. Results from this study showed very little variation in median slopes or R^2 values when stratified by GAP classes, regardless of the independent variable being evaluated. It is likely this occurred because individual pixel locations shifted in composition over time.

To help alleviate this problem, future research should choose a study area with ample ancillary data, such as a long term ecological research station. By applying the same methodology in this study to a location with a large availability of ancillary data it should be possible to evaluate how VI responses have changed in specific locations and if changes in species compositions are truly influencing regression trends, or if it is alternative factors operating. In this way basic rules for

how changes in parameters such as species composition, soil moisture, plant health and biomass could be evaluated in relation to changes in VI response and trends. Once these rules are established, it may be possible that alternate locations in similar ecosystems that experience the same trends in any given pixel may be undergoing the same changes on the ground, and less field data would be needed to validate findings.

Additionally, while this study has showed it is useful to segment the time series by season, it may also be useful to segment groups of years within the time series itself. For example, it is possible that a specific causal mechanism occurs at the very beginning of the time series (or some specific time step), and trajectories throughout the rest are influenced as a result. It is difficult to ascertain if these specific changes occur with the methods used here, but if analysis was segmented in five or ten year time steps which were evaluated separately then it would be easier to isolate when changes truly occurred.

It was hypothesized that topographic gradients were influential in determining trajectories of VI's due to their influence on soil water holding capacities, yet elevation was never analyzed as an independent variable. The reason for this is that in relatively flat environments elevation models need to have fine scale resolution (i.e. 1-meter), but this fine scale resolution does not match with the moderate resolution of the Landsat sensor. Therefore, to match the Landsat pixel size, 30-meter digital elevation models would need to be used to evaluate the influence of elevation on trajectories. On the SNG, 30-meter resolution elevation models are not accurate at capturing the fine scale variation, and therefore are inappropriate. To accurately capture the influence of elevation a satellite or airborne sensor with finer resolution would be required.

Lastly, there is uncertainty regarding the appropriateness of using linear models to assess temporal trends in VI's, which may not be exhibiting linear responses to particular independent variables. It is possible that non-parametric approaches would be more useful. To evaluate this, theil-sen regression was evaluated over the Complete Time Series using Running Days as the independent variable, and results were compared to those from ordinary least squares. Through this analysis it was found that results were nearly identical, and therefore non-parametric approaches and linear approaches perform similar

CHAPTER VI

CONCLUSION

The Sheyenne National Grassland is ecologically important for conservation because it represents the largest publicly owned tract of tallgrass prairie remaining in North America. Despite its designation as a National Grassland it is at risk from invasive species such as smooth brome, Kentucky bluegrass and leafy spurge, is likely effected by overgrazing, and there is uncertainty regarding how changes in climate will influence species composition. Because of these risks it is important for land managers to be able to identify threats to the health of the SNG, and to prioritize management actions. It is difficult for land managers to rely on field surveys alone to gather information about the health of the SNG because it is time consuming and expensive.

Remote sensing offers the ability to study ecosystem health across landscapes, and the release of the Landsat archive has enabled the characterization of Earth's conditions dating back to 1972, and at a moderate spatial resolution. The use of vegetation indices such as NDVI have long been used to assess conditions of Earth's surface. Using suites of VI's can provide further insight into ecosystem conditions, and these suites may be especially important in grassland ecosystems which have patchy and heterogeneous structures characterized by subtle transitions which require continuous monitoring.

Regression has been effective at monitoring subtle ecosystem changes in forested ecosystems, and this study has employed the same methods in a grassland ecosystem where significant trajectories were found. NDVI and NDII have increased between 1984 and 2011 on the SNG while RGR and SWIR32 have decreased. This indicates that greenness and vegetative moisture have increased while stress and non-photosynthetic vegetation have decreased.

For instance, it is likely that this increase in NDVI is associated with increases in spring precipitation acting in conjunction with cattle grazing which is selecting for the establishment of C₃ grasses, many of which are invasive. By reducing the vigor of native C₄ species which are less tolerant to grazing C₃ species have been competitively released. Additionally, C₃ species prefer wet springs which may be further encouraging their establishment.

In general, whenever one VI exhibited a specific temporal response, the rest of the VI's exhibited a similar response in the same predictable direction, and therefore trajectories could be assessed by solely evaluating the NDVI.

Significant changes occurred for all VI's through not only the Complete Time Series, but also through three different time segments throughout the growing season. Separating the growing seasons into individual regression models was useful to evaluate how locations which were known to consist of different compositions of C₃ and C₄ grasses have changed. For example, locations with larger compositions of C₄ grasses had smaller slopes in the Early Season which gradually became larger in the Peak Summer and Late Season. In contrast, locations with C₃ grasses had larger slopes in the Early Season which increased at a smaller rate in the Peak Summer and Late Season. Continuing to monitor how specific locations change throughout specific times of the growing season may be useful to identify when abundances of C₃ and C₄ grasses are shifting. Since

many of the invasive species on the SNG are C_3 , this may also enable identification of locations most in need of invasive species removal by land managers.

Characterizing gradual ecosystem changes is essential to evaluate grasslands, and this study has shown the regression can be effectively used to quantify the direction and magnitude of change. Additionally, evaluation of p-values is useful to determine if change is significant or not. Continued monitoring of grasslands with remote sensing will be useful for land managers to determine locations where actions should be prioritized, and as additional sensors, such as Sentinel-2 become available the temporal coverage and spatial and spectral resolutions for this type of analysis will improve the ability to monitor these ecosystems.

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