Patterns of greenness (NDVI) in the Southern Great Plains and their influence on the habitat quality and reproduction of a declining prairie grouse

by

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Abstract

Patterns of vegetative greenness and timing of greenness events have been a strong predictor of habitat availability and space use for several species of wildlife and may be a particularly useful tool for imperiled grassland species such as the lesser prairie-chicken (*Tympanuchus pallidicinctus*). I evaluated the utility of Normalized Difference Vegetation Index (NDVI) and NDVI-based vegetation phenology metrics in estimating lesser prairie-chicken habitat availability, habitat quality, and space use during the reproductive season.

I captured, marked with GPS and VHF transmitters, and monitored lesser prairie-chicken nest and brood locations during the reproductive season in Kansas during 2013-2015. I acquired Landsat 8 and vegetation phenology metric data from eMODIS Remote Sensing Phenology (RSP) satellite imagery during 2013-2015. Using NDVI and vegetation phenology data at nest and brood locations, I first examined the use of these remotely sensed tools to model habitat selection and predicted habitat availability. I then tested relationships among phenology metrics and reproductive success (e.g., nest and brood success) and assessed timing of nest initiation and hatch relative to patterns of greenness. Last, I investigated correlations between phenology metrics and in-situ vegetation measurements and stocking density.

Nest site-selection was best predicted by Time Integrated NDVI (TIN), with probability of use increasing as values of TIN increased ($\beta = 2.897$, SE = 1.049). The TIN metric is a proxy for the density of overhead vegetation cover. Brood site-selection was best predicted by an Amplitude (AMP) * Year model ($\beta_{AMPscale1} = 7.76$, SE = 4.81, $\beta_{2014} = 0.99$, SE = 2.065, $\beta_{2015} = -1.78$, SE = 2.17, $\beta_{AMPscale1:2014} = -1.79$, SE = 5.12, $\beta_{AMPscale1:2015} = 6.32$, SE = 5.47), with probability of use varying among years but increasing as values of AMP increased. The AMP

metric describes the total increase in productivity from the start of the growing season to the peak of the growing season. Areas experiencing greater increases in productivity were more likely to be used by brood-rearing females.

To predict nesting and brood-rearing habitat abundance in Kansas, I used a random forest approach. Ultimately, I was unable to predict nesting habitat availability using phenology metrics due to high out-of-bag error (30.48%) and high class error rates, with non-habitat predicted as habitat ~63% of the time. Fortunately, I was able to predict brood-rearing habitat abundance. Informative brood habitat variables selected by the random forest model included the End of Growing Season Time (EOST) at the 1-km scale, TIN at the 1-km scale, AMP at the 370-m scale, percent grassland within 5-km, End of Season NDVI (EOSN) at the 1-km scale, density of county roads within 2-km, density of oil wells within 2-km, Time of Maximum NDVI (MAXT) at the 1-km scale, Start of Growing Season Time (SOST) at the 250-m scale, and the density of transmission lines within 2-km. Using the selected variables, I identified priority habitat using the Kappa threshold and high priority habitat using the Sensitivity Specificity Sum Maximizer threshold. Habitat availability was variable between years, with a 71% and 51% decrease in priority and high priority habitat, respectively, from 2014 to 2015. I identified 2,154,137.5 ha of priority habitat and 8,225 ha of high priority habitat for 2014. I identified 636,493.75 ha of priority habitat and 3,993.75 ha of high priority habitat for 2015.

Nest survival was best predicted by MAXT at the 500-m scale, with nest survival maximized when MAXT was Day-of-Year (DOY) 160 (June 9) and decreasing linearly as MAXT increased ($\beta = -0.009$, SE = 0.004). Similarly, I identified phenological differences at successful and unsuccessful nest and brood sites. At successful nest sites, TIN was greater than at unsuccessful nests ($p = 0.05$), and MAXT occurred earlier than at unsuccessful nests (p =

0.04). At successful brood sites, MAXT occurred later and EOSN was greater than at unsuccessful brood sites (p = 0.003). The EOSN metric was also significantly different, with EOSN greater at successful brood sites than at unsuccessful brood sites (p = 0.01).

Timing of nest initiation and hatch relative to patterns of greenness indicated that first nests were initiated within ~20 days of SOST. All hatch dates occurred before the peak of the growing season date (MAXT). Ultimately, lesser prairie-chickens time nest initiation and hatch between the start of the growing season and peak of the growing season.

I also tested correlations among vegetation phenology metrics to in-situ vegetation measurements and stocking densities. Correlations with phenology metrics and in-situ vegetation measurements varied among years, but TIN and AMP were often positively correlated with measures of visual obstruction at multiple scales and cover of forbs and grasses (r = 0.02 – 0.51). The TIN, AMP, and Maximum NDVI (MAXN) metrics were often negatively correlated (r = -0.02 – -0.15) with cover of bare ground, litter depth, litter cover, and shrub cover. Last, I evaluated linkages between vegetation phenology metrics and cattle stocking density. Correlations varied among years (2014 and 2015). The TIN and AMP metrics were positively correlated with stocking density in 2014 (r = 0.13, r = 0.07, respectively); yet TIN was negatively correlated with stocking density in 2015 (r = -0.17) and AMP was not correlated with stocking density in 2015.

Ultimately, I provide evidence that NDVI-based vegetation phenology metrics can be used to model habitat use and predict habitat availability for lesser prairie-chickens in Kansas. My predictions from phenology-based metrics indicated that the availability of high priority habitat may be limited. I also provided evidence that phenology metrics correlate to in-situ vegetation measurements and stocking densities, making phenology metrics a promising tool for monitoring lesser prairie-chicken habitat remotely.

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Dedication

To my grandparents, for always believing in me and for their unconditional support and love.

Chapter 1 - MODIS-based Vegetation Phenology Metrics Influence Resource Selection and Prediction of Habitat Availability

Introduction

The Normalized Difference Vegetation Index (NDVI) is a remotely sensed index that calculates the difference between the amount of red and near infrared light reflected off living vegetation, which effectively estimates the “greenness” of vegetation (Rouse et al. 1974, Tucker 1979). Simply put, NDVI can provide insight into the health, vigor, and density of living vegetation and is used to evaluate phenological conditions over time. Results are bounded between 1 and -1 with negative values representing snow, water, or barren landscapes and positive values representing light, moderate, or densely vegetated areas such as forests or agricultural plots (USGS 2021a). Grasslands and shrublands, for example, trend towards moderate NDVI values between 0.2-0.5 (USGS 2021a); although this can vary depending on the structure and density of vegetation (Paruelo and Lauenroth 1995). Although NDVI is well-known to be useful for modeling phenological patterns and vegetation characteristics, its utility in evaluating wildlife habitat needs further exploration, particularly for grassland wildlife.

Use of NDVI grew rapidly following its development in the early 1970s, with research focusing on assessing vegetation productivity and vigor. In the Great Plains, the first reported use of NDVI was by Rouse et al. (1974), where NDVI was calculated using Landsat 1 Multispectral Scanner (MSS) images to investigate the health of grasslands across the Great Plains. Some of the first wildlife-related studies linked NDVI to habitat use by large herbivores (Pettorelli et al. 2011). More recently, use of NDVI and remote sensing in avian studies has become commonplace (e.g., Gottschalk et al. 2005, Pettorelli et al. 2011). Several avian studies used remotely sensed NDVI-based metrics to investigate species richness (Hurlbert and Haskell 2003, Bino et al. 2008, St-Louis et al. 2009, Vogeler et al. 2014), migration (Saino et al. 2004a, Saino et al. 2004b, Robson and Barriocanal 2010), and reproduction (Ross et al. 2017, Poessel et al. 2020, Stoner et al. 2020). Given that grassland bird species have declined >70% in the last 50 years (Rosenberg et al. 2019), it is important to explore the utility of NDVI to inform conservation of at-risk grassland birds. One such species that may benefit from a NDVI-based study is the lesser prairie-chicken (*Tympanuchus pallidicinctus*).

The lesser prairie-chicken is a grassland obligate species whose range spans 5 states and 4 ecoregions as described by Van Pelt et al. (2013) and McDonald et al. (2014). The occupied range of lesser prairie-chickens is estimated to have declined by 85% over the last 100 years with abundance remaining low in large portions of their range (McDonald et al. 2014, Boal and Haukos 2016, Garton et al. 2016). Declines are due, in part, to the degradation of remaining grasslands through the alteration of ecological drivers such as fire, grazing, and precipitation (Askins et al. 2007) and historic and ongoing conversion of native grasslands to cropland (Taylor and Guthery 1980, Askins et al. 2007, Rodgers 2016, Dahlgren et al. 2016). Of the ecological drivers (drought, grazing, fire), drought is predicted to increase in intensity and frequency as climate change progresses, potentially exacerbating the decline of grassland bird populations (Peterson 2003, Strzepek et al. 2010, Cook et al. 2015, Grisham et al. 2016, USFWS 2021). Such climate issues, among others, have compounded and resulted in a 2019 lawsuit demanding the U.S. Fish and Wildlife Service (USFWS) to decide on the 2016 petition to list the lesser prairie-chickens under the 1973 Endangered Species Act (ESA). After ~2 years of investigation, the USFWS determined that the remaining lesser prairie-chickens would be split into 2 Distinct

Population Segments (DSP) and listed under the ESA. The Southern DSP is currently classified as endangered while the Northern DSP is classified as threatened (USFWS 2022).

Population declines, degradation of remaining habitat, and a recent listing under the ESA make monitoring lesser prairie-chickens critical for species recovery. Field-based research has provided wildlife managers with invaluable information regarding habitat requirements and limiting factors influencing population growth (Pitman et al. 2006, Hagen et al. 2009, Grisham 2012, Van Pelt et al. 2013, Haukos and Zavaleta 2016). For example, an understanding of field-based habitat requirements at nest and brood sites are well documented, such as greater vertical structure between 2.0 and 3.5 dm at 75% visual obstruction at nest sites, less bare ground, and greater percentages of litter compared to what is available at random sites (Giesen 1994, Pitman et al. 2005, Patten and Kelly 2010, Lyons et al. 2011, Hagen et al. 2013, Fritts et al. 2016, Grisham et al. 2016, Lautenbach et al. 2019). However, broad-scale monitoring of lesser prairie-chicken habitat using field-based measurements is time consuming, costly, and difficult. It is challenging to evaluate habitat through on-the-ground measurements due to the importance of subtle structural characteristics in grasslands that are needed over broad scales to provide quality habitat (Gehrt et al. 2020). Given the importance of grassland-dominated landscapes for lesser prairie-chicken reproduction and persistence, there is a need to identify the availability of reproductive habitat across their current distribution, as well as conserve what remains (Hagen et al. 2004). This is not a feasible undertaking with field-based measurements alone. Approaches that use remote sensing technology and satellite imagery are a promising option in need of further evaluation.

The objective of my study was to evaluate the influence of NDVI and NDVI-based vegetation phenology metrics on nest site-selection, brood site-selection, and reproductive habitat abundance in the Mixed-Grass Prairie and Short-Grass Prairie/Conservation Reserve Program (CRP) Mosaic ecoregions of western Kansas. I predicted that probability of use would be greater at nest sites with higher NDVI at the time that laying occurs (snapshot NDVI). Lesser prairie-chicken nests are typically comprised of both living and residual cover (Lautenbach et al. 2019); thus, I expected the presence of more living cover to result in higher NDVI at the time of laying compared to what is available. Additionally, I expected nest-site selection to be predicted by a quadratic relationship with the NDVI-based phenology metric Amplitude. As previously mentioned, lesser prairie-chicken nests are typically constructed under living and residual cover (Lautenbach et al. 2019). Given that NDVI only measures the reflectance from living vegetation, I expected a quadratic relationship with Amplitude in the 0.3-0.4 range to represent that combination of living and residual cover. In terms of brood-site selection, I predicted a positive linear relationship with the phenology metric Maximum NDVI. Maximum NDVI is the value of NDVI at the peak of the growing season and has been related to brood use and optimal food availability (arthropods and vegetation) for other grouse species (i.e., *Lagopus leucura* and *Centrocercus urophasianus*; Wann et al. 2019, Stoner et al. 2020). Given the associations between maximum NDVI and food availability, I expected females with broods to choose sites with greater maximum NDVI values. Lastly, I predicted that the combination of gradient landscape variables and phenology metrics would result in an accurate prediction of reproductive habitat availability in Kansas through the use of a random forest model. Currently and without the use of vegetation phenology variables, we can predict habitat based on the distribution of large grassland dominated areas with limited anthropogenic structures (Sullins et al. 2019). However, we cannot yet predict habitat within those large grassland dominated areas. I expected that a random forest classification model using NDVI phenology metrics and gradient landscape variables as predictors would predict habitat availability within grasslands.

Methods

I evaluated the influence of snapshot NDVI images and 9 vegetation phenology metrics on nest- and brood-site selection by lesser prairie-chickens. I also evaluated the importance of these metrics at multiple scales relative to nest and brood locations. Lastly, I incorporated vegetation phenology metrics and landscape scale variables into a random forest model to predict the availability of lesser prairie-chicken reproductive habitat in western Kansas.

Study Area

My study area was the result of pooled data previously collected in portions of western Kansas. The study area covers 2 of the 4 ecoregions occupied by the lesser prairie-chicken: the Mixed-Grass Prairie and the Short-Grass Prairie/CRP Mosaic (Figure 1.1; McDonald et al. 2014, Boal and Haukos 2016). Fire, grazing, and precipitation/drought events are the most common ecological disturbances and drivers across this range, though all of these regimes have shifted in frequency and intensity over the last 100 years (Askins 2007). Drought specifically is a common disturbance that is predicted to increase in frequency and intensity as climate change progresses (Strzepek et al. 2010, Grisham et al. 2016). Across the lesser prairie-chicken range, there is also a distinct longitudinal precipitation gradient of declining mean annual average precipitation from east to west. In the easternmost portion of the lesser prairie-chicken range, mean annual precipitation ranges between 63.9 and 76.3 cm (Grisham et al. 2016). In the westernmost portions of the LEPC range, mean annual precipitation ranges between 27.8 and 40.5 cm

(Grisham et al. 2016). Weather is also highly variable with year-to-year variation in annual precipitation and thus variability in aboveground net primary productivity (Sala et al. 1988).

Within the Mixed-Grass Prairie Ecoregion, there were 2 study sites: Clark (located in Clark County) and Red Hills (located in Kiowa and Comanche counties). The Red Hills study site was located in the easternmost portion of the LEPC range, receives greater annual precipitation compared to other sites, and included rotational and patch-burn grazing as management practices. Soil composition in the Red Hills was mostly sandy loam, clay loam, and clay; soil composition in the Clark County study site was primarily fine sandy loams, fine sands, and loamy fine sands (Sullins et al. 2018a). Dominant vegetation in both study sites included grasses such as little bluestem (*Schizachyrium scoparium*), sand dropseed (*Sporobolus cryptandrus*), alkali sacaton (*Sporobolus airoides*), blue grama (*Bouteloua gracilis*), big bluestem (*Andropogon gerardii*), switchgrass (*Panicum virgatum*), and sideoats grama (*Bouteloua curtipendula*). Abundant forbs included western ragweed (*Ambrosia psilostachya*), kochia (*Kochia scoparium*), Russian thistle (*Salsola* sp.), broomweed (*Amphiachyris dracunculoides*), broom snakeweed (*Gutierrezia sarothrae*), and Louisiana sagewort (*Artemisia ludiviciana*). Lastly, common shrubs included sand sagebrush (*Artemisia filifolia*), sand plum (*Prunus angustifolia*), eastern redcedar (*Juniperus virginiana*), and fragrant sumac (*Rhus aromatia*; Sullins et al. 2018a, Gulick 2019, Lautenbach et al. 2019).

Within the Short-Grass Prairie/Conservation Reserve Program (CRP) Mosaic Ecoregion, there was one study site labeled as the Northwest study site, which encompassed Logan and Gove counties. Although this was classified as the short-grass prairie, inclusion of CRP lands provided both mixed and short grasses in this region. Dominant land uses across this portion of the study area included grazing, CRP grasslands, and row-crop agriculture. Dominant grasses included blue and hairy grama (*Bouteloua hirsuta*), little bluestem, buffalograss (*Bouteloua dactyloides*), big bluestem, sideoats grama, and western wheatgrass (*Pascopyrum smithii*). Common forbs included Russian thistle, western ragweed, broom snakeweed, annual buckwheat, prairie sunflower (*Helianthus petiolaris*), and nine-anther dalea (*Dalea enneandra*). Dominant shrubs included sand sagebrush and yucca (*Yucca* sp.; Sullins et al. 2018a, Lautenbach et al. 2019).

Remotely sensed data acquisition and processing

I examined the utility of Landsat 8 images from one moment in time (e.g., snapshot) and time series AQUA eMODIS Remote Sensing Phenology (RSP) imagery to predict lesser prairie-chicken habitat.

Landsat 8:

To assess NDVI at the nest site in real time, I acquired remote data from the Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS). This is an open-source satellite operated jointly by the U.S. Geological Survey (USGS) and the National Aeronautics and Space Administration (NASA). For this research, I accessed Landsat 8 data using the EarthExplorer (https://earthexplorer.usgs.gov/) interface. Landsat 8 provides users with 9 spectral bands, a moderate pixel resolution of 30 m, a repeat cycle of 16 days, and a scene size of 185 km x 180 km (NASA 2021, USGS 2021b). Scene size refers to the area scanned in each image; a scene size of 185 km x 180 km covers multiple study sites at once. Landsat 8 data comes in 2 levels: level 1 and level 2. I used Level 2 data in this research, which are referred to as Surface Reflectance products. Surface Reflectance scenes are atmospherically corrected by the U.S.

Geological Survey Earth Resources Observation and Science (EROS) Center and any potentially detrimental effects such as atmospheric scattering from aerosols will not affect the images used and derived estimates of NDVI (USGS 2021c).

AQUA MODIS:

To evaluate the effect of phenology metrics on reproduction, I used imagery from the Aqua Moderate Resolution Imaging Spectroradiometer (hereafter MODIS) satellite, where Aqua is the satellite and MODIS is the imaging sensor. Specifically, I used the C6 Aqua Western 250 m eMODIS RSP (remote sensing phenology) data, downloaded from the USGS Phenology Viewer (Jenkerson et al. 2010, Brown et al. 2015; https://doi.org//10.5066/F7PC30G1), where 250 m refers to the pixel size. USGS recommends using the Aqua satellite instead of the second Terra satellite for analyses after 2007 due to sensor degradation of Terra (USGS 2021d). Images from the fully functioning Aqua Satellite have been processed into time-series phenology metrics known as C6 Aqua eMODIS Remote Sensing Phenology (RSP) data. Nine phenology metrics were developed based on spatially explicit variation of weekly NDVI composites and are maintained and processed by EROS and calculated for the contiguous United States. The 9-phenology metrics included amplitude (AMP), Duration (DUR), End of Season NDVI (EOSN), End of Season Time (EOST), Maximum NDVI (MAXN), Time of Maximum (MAXT), Start of Season NDVI (SOSN), Start of Season Time (SOST), and Time Integrated NDVI (TIN; https://doi.org//10.5066/F7PC30G1; Table 1.1). In this study, I extracted phenology metrics from the western United States extent as all study sites were within this extent.

Although AQUA MODIS images are typically ready-to-use, I performed additional pre-processing actions prior to completing any analyses. Within each MODIS image, there are cells where data were unable to be calculated during EROS analyses, and cells that represent water. Cells where data were unable to be extracted are given a value of either 0 or -1000 and cells that represent water are given values of either 255 or 1000. I set cells with values of 0, 255, -1000, and 1000 to “No Data” using the “Set Null” function in ArcMap 10.8 so that values from these cells would not be included in any analyses. After cells were converted to “No Data”, I used focal statistics to calculate the mean of the 9 vegetation phenology metrics (Table 1) at 4 scales for each phenology image. The 4 scales that I used were 370 m, 500 m, 1 km, and 3 km. These scales represent the average daily displacement of females during the reproductive season, as well as general space use at broader scales. The resulting rasters were used to extract mean values of phenology metrics around nest, brood, and random points.

Nesting and brood data acquisition:

Nesting data were pooled from prior studies in Kansas in 2013, 2014, and 2015. At the beginning of each breeding season, I captured female lesser prairie-chickens using drop nets and walk-in funnel traps from mid-March to mid-May (Haukos et al. 1990, Silvy et al. 1990). I marked captured females with either a 15-g very-high-frequency (VHF) transmitter (Advanced Telemetry Systems, Isanti, MN, USA) or a 22-g solar powered GPS satellite transmitter (PTT-100, Microwave Telemetry, Inc., Columbia, MD). The GPS transmitters recorded female locations every 2 hours between 0500-2300, whereas females marked with VHF transmitters were tracked manually and triangulated 3-4 times per week.

To determine when a nest was initiated, I evaluated the spatial patterns of lesser prairie-chickens during the breeding season. Nesting behavior of a GPS-marked female was indicated by multiple transmitted locations at the same point and minimal movement around that point. For

VHF-marked females, a nest was deemed initiated if the female was located in the same spot >3 times in a row. In this research, “nest initiation” refers to the initiation of laying. Following confirmation of laying, females were flushed from the nest to count, weigh, measure, and float eggs to ascertain an estimated hatch date. I recorded the Universal Transverse Mercator coordinate system locations of each nest using the WGS 1984 Zone 14N datum. As the nesting season progressed, nests were visited a second time once the female left the area to determine the outcome of the nest (successful or failed). If a nest was successful, I monitored and flushed the adult female and brood weekly starting at either 7- or 14-days post-hatch and continued flushing broods at the 21st, 28th, and 35th day post-hatch (Parker 2021). Occasionally, brood flushes could not be completed on those exact days due to inclement weather or lack of GPS points for that morning (Parker 2021). I recorded the location of each weekly brood flush in Universal Transverse Mercator coordinate system using WGS 1984 Zone 14N.

Gradient Landscape Variables

To inform spatial predictions of habitat availability, I acquired gradient landscape spatial layers from Sullins et al. (2019) that were known to predict lesser prairie-chicken distributions. First, I acquired estimates of percent grassland within a 5 km radius derived from National Land Cover Database (NLCD) 2011 layers by Sullins et al. (2019), as well as layers depicting anthropogenic feature densities within 2 km. Anthropogenic feature variables included densities of oil wells, county roads, major roads, transmission lines, and cell phone towers.

Nest site-selection:

Snapshot NDVI:

I evaluated the influence of snapshot NDVI (NDVI at the start of laying) on nest-site selection using a logistic regression framework in Program R and an information theoretic approach as a method of model selection (Akaike's Information Criterion adjusted for small sample size; AICc; Burnham and Anderson 2002, R Core Development Team 2022). I compiled a list of nest laying dates from 120 nests (including first, second, and third nest attempts) from 2013-2015 at the Clark, Northwest, and Red Hills study sites. Next, I searched for Landsat 8 OLI/TIRS scenes with acquisition dates that corresponded to the laying date of each nest, or within one week of the laying date. Landsat 8 images have a revisit period of 16 days, which presented a challenge: many images were not available on the exact laying date for each nest. Additionally, one major limitation of satellite imagery is the negative effects of cloud cover, which interrupts the reception of reflected light read by the satellite sensor and negatively impacts calculations of NDVI. Therefore, I searched for images that fell within one week of the laying date. If no image within one week of the laying date was available, the nest was excluded from analyses. Similarly, any nests that fell under cloud cover were also excluded from analysis, unless another image was available within one week of the laying date.

In each Landsat 8 scene, I calculated NDVI using the raster calculator in ArcGIS 10.8 (ESRI, Inc., Redlands, CA, USA) with the following equation:

$$NDVI = Float\ (Band\ 5 - Band\ 4)\ /\ Float\ (Band\ 5 + Band\ 4)$$

Band 5 is the Near Infrared band (wavelength 0.85-0.88 micrometers) and Band 4 is the Red band (wavelength 0.64-0.67 micrometers). The NDVI calculation measures the difference between the amount of red and near infrared light being reflected off living vegetation. The resulting NDVI calculation is unitless and measured on a scale from 1 to -1. Positive values approaching 1 indicate dense vegetation cover, such as a forest or agricultural plot. Values approaching -1 indicate water, and values around 0 indicate barren landscapes (Neigh et al. 2008, Huang et al. 2020). Grasslands and shrublands typically result in NDVI values between 0.2 and 0.5 (USGS 2021a); though this can vary depending on vegetation structure and composition (Paruelo and Lauenroth 1995).

I converted Excel worksheets containing each nest location into shapefiles, and loaded these into their respective Landsat 8 images. Next, I generated a 3.2 km buffer around each nest location, as this is the average distance that most females will nest from an active lek (Boal and Haukos 2016). Within these buffers, I generated 2 random points per used point. Random points were generated exclusively within grasslands and shrublands, as these are the primary cover types used by lesser prairie-chickens during the reproductive season. Lastly, I used the "Extract Multi-value to Point" tool in the Spatial Analyst toolbox to extract snapshot NDVI values at used and random points.

Following data extraction, I constructed a candidate model set containing 7 *a priori* models. Variables tested in these models included snapshot NDVI, quadratic snapshot NDVI, additive and interactive models using snapshot NDVI, site, year, and a null model (Table 1.2).

MODIS Vegetation Phenology Metrics:

To test the influence of NDVI-based vegetation phenology metrics on nest-site selection, I used C6 Aqua Western 250 m eMODIS RSP images and extracted phenology metrics at multiple scales around nest and random points using the "Extract Multi Values to Point" tool in ArcGIS 10.8 (ESRI, Inc., Redlands, CA, USA). I extracted values at the 250-m pixel scale and at 4 additional scales (370 m, 500 m, 1 km, and 3 km) around nest and random sites. Following data extraction, I constructed one candidate model set containing 43 *a priori* models that incorporated the 9 phenology variables at multiple scales. Variables tested in the model set included single-variable phenology metrics at all scales, quadratic models, and additive and interactive combinations of these variables (Table 1.3). Snapshot NDVI was not included as a variable due to the differences in sample size. Given that I matched Landsat 8 scenes to nest laying dates and eliminated nests that fell within cloud cover, there were fewer nests used to fit the snapshot NDVI models. Conversely, all available nests were included in the phenology model set, so long as they had recorded GPS coordinates.

Brood-site selection:

I used a logistic regression framework using generalized linear models to evaluate the influence of 9 vegetation phenology metrics at 5 scales on the brood-site selection by female lesser prairie-chickens. Using ArcGIS version 10.8 (ESRI, Inc., Redlands, CA, USA), I imported coordinates of 408 brood locations during 2013-2015 from 3 study sites (Clark, Northwest, and Red Hills). I generated 2 paired random points per used point for a total of 816 random points. Paired random points were located exclusively within grasslands and shrublands, as this is the primary land cover used during brood-rearing. I then extracted the values of each phenology metric at multiple scales around brood and random points using the “Extract Multi Values to Point” tool. I also extracted values at 4 additional scales (370 m, 500 m, 1 km, and 3 km) around brood and random points.

Once data were extracted, I constructed 34 *a priori* logistic regression models to test the influence of vegetation phenology metrics on brood-site selection. Models included single variables, multi-variables, quadratic relationships, and site and year interactions (Table 1.4).

Evaluation of generalized linear models and covariates:

Models of nest- and brood-site selection were evaluated using Akaike's Information Criterion adjusted for small sample size (AICc; Burnham and Anderson 2002). Models within 2 ΔAICc of the top-ranked model were considered competitive. Additionally, I evaluated beta coefficients to further assess the relative importance of predictor variables, and generated probability of use curves to visualize results. Beta coefficients with overlapping 95% confidence intervals were considered uninformative.

Predicting reproductive habitat abundance:

To predict lesser prairie-chicken reproductive habitat availability in Kansas based on vegetation phenology and gradient landscape variables, I used a random forest approach (Breiman 2001) using package "randomForest" in Program R (R Core Development Team 2022, Liaw and Wiener 2002). I combined 2014 and 2015 nesting data and brood-rearing data to determine the most informative set of variables among years.

Random forest is a type of classification and regression tree algorithm that evaluates the importance of input variables and finds the most parsimonious and accurate predictions based on bootstrapping several trees that are then validated using out-of-bag error. Out-of-bag error rates are typically estimated based on bootstrapping a training data set and leaving 1/3 of the sample aside to validate the model. Random forests modeling can provide more accurate predictions compared to other regression-based classifiers such as logistic regression when interactions between variables and nonlinear relationships with response variables are prevalent (Cutler et al. 2007). Given its utility and my expectation of having numerous quadratic/nonlinear relationships with predictors, I expected random forests to be a useful tool in predicting reproductive habitat availability in Kansas.

As input variables, I included 9 vegetation phenology metric rasters (Table 1.1) at 5 scales (250 m pixel scale, 370 m, 500 m, 1 km, and 3 km) around nest and brood points, and 5 gradient landscape variables (percent grassland within 5 km, density of oil wells within 2 km, density of county roads within 2 km, density of transmission lines within 2 km, and density of vertical structures not including powerlines within 2 km). Importantly, random forest approaches require input rasters to be of the same scale and extent. To address this, I resampled the landscape variable rasters from a 30-m pixel resolution to 250-m resolution to be consistent with the scale of the phenology based metric rasters.

Once all values were extracted from rasters at all used and available locations, I fit random forests models and performed variable selection. I removed variables correlated at $\alpha = 0.05$ from inclusion in the same models. Random forests remain powerful even when variables of low importance are included in the model, and cross-validated accuracy is not significantly improved when unimportant variables are removed (Fox et al. 2017). Thus, all uncorrelated variables were included in the random forest model to predict nesting and brood-rearing habitat availability and provide inference on the relative importance of each predictor.

Lastly, I estimated occurrence thresholds using the Kappa statistic and sensitivity-specificity sum maximizer following Jimenez-Valverde and Lobo (2007). The Kappa statistic is typically considered a weaker performing estimator compared to the sensitivity-specificity sum maximizer, in that it often overestimates (and in some cases underestimates) species distribution. While recognizing this, I decided to use the Kappa statistic as a broader representation of potential priority habitat, and used the sensitivity-specificity sum maximizer as a more accurate representation of high priority grasslands for lesser prairie-chicken reproductive habitat availability.

Using the thresholds derived from the Kappa and sensitivity-specificity sum maximizer statistics, I generated 2 binary rasters per year to identify priority reproductive habitat and high priority reproductive habitat, respectively. Next, I used the Extract by Mask tool in ArcGIS version 10.8 (ESRI, Inc., Redlands, CA, USA) to extract the number of pixels within the binary rasters that occurred within grasslands to calculate the area of habitat in hectares.

Results

Nest site-selection:

Using a logistic regression framework, I evaluated the influence of snapshot NDVI on nest-site selection based on a sample of 120 nests and 240 random points. Snapshot NDVI, based on the laying date of nests, was not a reliable predictor of nest site-selection. Although the single variable snapshot NDVI ($\beta = -0.52$, SE = 0.985) model was within 2 ΔAICc of the null model and carried 22% of AICc weight, beta coefficients overlapped 0 at the 95% confidence interval (Table 1.2).

In contrast, NDVI-based phenology metrics were informative predictors of nest-site selection. I used values from 237 nests and 474 available random points to fit logistic regressions. The single variable Time Integrated NDVI (TIN) model at the 250-m pixel scale was a reliable predictor of nest site-selection and carried 12% of model weight ($\beta = 2.897$, SE = 1.049; Table 1.3), with probability of use increasing with greater TIN values (Figure 1.2). There were 6 models within 2 ΔAICc of the top-ranked model. The second-ranked model, which carried 7% of model weight, was TIN + AMP ($\beta_{TIN} = 2.372$, SE = 1.18, $\beta_{AMP} = 1.398$, SE =

1.414). Although the TIN variable in this model was informative at the 95% confidence interval, the AMP variable was not. Thus, I determined that the inclusion of the AMP variable was spurious and did not improve predictive power over the top-ranked model. The 5 other competitive models were also not informative at the 95% confidence interval, though it is important to note that 3 of the 5 models included TIN as an informative variable, which further emphasized TIN's ability to predict nest-site selection (Table 1.3).

Brood site selection:

I used phenology metrics from 408 brood sites and 816 available points. Results indicated that the interactive Amplitude at the 370-m scale*Year model was a reliable predictor of brood-site selection ($\beta_{AMPscale1} = 7.76$, SE = 4.81, $\beta_{2014} = 0.99$, SE = 2.065, $\beta_{2015} = -1.78$, SE = 2.17, $\beta_{AMPscale1:2014} = -1.79$, SE = 5.12, $\beta_{AMPscale1:2015} = 6.32$, SE = 5.47; Figure) and carried 74% of AICc weight, with probability of use increasing as AMP increased (Table 1.4, Figure 1.3). The AMP 370-m variable in this model was informative at the 85% confidence interval, though year interactions were not informative at the 85% confidence interval. Notably, however, the slope associated with probability of use in 2015 was steeper than slopes associated with probability of use in 2014 and 2015 (Figure 1.3). The single variable AMP 370-m model ($\beta = 6.86$, SE = 1.24) carried 3% of model AICc weight and remains informative at the 95% confidence interval and further confirms the importance of Amplitude at the 370-m scale as a variable (Figure 1.4). Overall, females with broods selected sites with greater AMP values 370 m around brood sites compared to what was available.

Predicting reproductive habitat availability:

Nest Habitat

When predicting nest habitat abundance, 10 uncorrelated variables were selected for the final model (Figure 1.13). The 3 most important variables in this random forest model were phenology metrics. Amplitude at the 1 km scale (scaled variable importance of 0.024), Time Integrated NDVI (TIN; scaled variable importance of 0.018) at the 1 km scale, and End of Season Time (EOST; scaled variable importance of 0.017) at the 1 km scale were the 3 most important variables. In order of importance, the remaining selected variables were: Start of Season Time at the 1 km scale (SOST; scaled variable importance of 0.016), End of Season NDVI at the 1 km scale (EOSN; scaled variable importance of 0.015), density of county roads within 2 km (0.015), percent grassland within 5 km (scaled variable importance of 0.015), Time of Maximum NDVI at the 1 km scale (MAXT; scaled variable importance of 0.010), density of oil wells within 2 km (scaled variable importance of 0.006), and density of transmission lines with 2 km (scaled variable importance of 0.000003). Notably, scaled variable importance values were much lower for all variables included in the nest random forest model compared to those included in the brood random forest model, indicating weak predictive power and low relative contribution to the final model. Out-of-bag (OOB) error rates were also greater by 19.95% in the nest model, with an OOB rate of 30.48%, further emphasizing the inaccuracy of this model. Similarly, class errors were much higher in this model, with non-habitat being predicted as habitat ~63% of the time.

Given the low predictive power of the nest habitat model and the high error rates, I decided to not plot the partial probability plots describing predicted use. I also did not plot the predictive surfaces for nest habitat abundance. However, measures of model accuracy were quite high. The overall accuracy (PCC) of the random forest nest model was 99.82%, the sensitivity was 100%, and the specificity was 99.73%, which may be pointing to overfitting due to a small sample size.

Brood Habitat

For my brood random forest model, 3 phenology metrics carried the majority of variable importance (Figures 1.5, 1.6) and outcompeted gradient landscape variables. After evaluating multicollinearity based on $\alpha = 0.05$, 39 phenology metrics at multiple scales were removed from consideration. End of Season Time (EOST) at the 1 km scale was the most important variable as indicated by scaled variable importance (0.09; Figure 1.5), with greater probability of use occurring at locations with early-mid October end of season dates. This was followed closely in importance by Time Integrated NDVI (TIN) at the 1-km scale (scaled variable importance = 0.079) and Amplitude (AMP) at the 370-m scale (scaled variable importance = 0.078; Figure 1.5). Probability of use was greatest when TIN was > 0.35, and lowest at TIN values < 0.35 (Figure 1.6). Probability of use was lowest when AMP was between 0.2-0.3 but increased rapidly as AMP increased past 0.3 (Figure 1.6).

Following the 3 phenology-based metrics, percent grassland within 5 km was ranked fourth in variable importance. Percent grassland ranked higher than other landscape variables and carried a scaled variable importance of 0.07. Probability of use peaked at ~77% grassland within 5 km but was similarly high in the presence of ~50% grassland within 5km (Figure 1.6). Between these 2 percentages, however, probability of use decreased.

The fifth variable of importance was End of Season NDVI (EOSN) at the 1-km scale with a scaled variable importance of 0.066. Here, probability of use was greatest at EOSN values between 0.25-0.33, and rapidly declined at EOSN values > 0.35. After EOSN, density of county roads within 2 km was selected (scaled variable importance of 0.066), with probability of use peaking around 40. Density of oil wells within 2-km was similarly important (scaled variable importance of 0.054). Here, however, probability of use was greatest when the density of oil wells within 2 km was between 0-2, and rapidly declined as the number of oil wells increased (Figure 1.6).

The third to last ranked variable in this model was Time of Maximum NDVI (MAXT) at the 1-km scale (scaled variable importance of 0.044). Probability of use first peaked at MAXT 160, which is in early June. Probability of use decreases past this date, but increased again after MAXT reaches 200, which is in mid-July. The greatest probability of use occurred when MAXT was from 235-250, which includes mid-August through early September. The second to last variable in this random forest model was the Start of Growing Season Time (SOST) at the pixel scale (250 m) with a scaled variable importance of 0.034. Probability of use was near 0 from day -150 up until day 100. Past day 100, probability of use sharply increased (Figure 1.6).

The final and subsequently least important variable in this random forest model was density of transmission lines (scaled variable importance = 0.0006). Here, a similar relationship to density of oil was observed, where probability of use was greatest when there were 0 transmission lines and rapidly declined as the number of transmission lines increased (Figure 1.6).

The resulting predictive surface of brood-rearing habitat availability in Kansas ranged from low probabilities of use (0.16) to high probabilities of use (0.73) in 2014 (Figure 1.7). In

2015, the resulting predictive surface of brood-rearing habitat abundance in Kansas ranged in probabilities of use from 0.12 – 0.76 (Figure 1.10). Based on the 2 predictive surfaces that incorporated phenology metrics and landscape variables, I derived 2 estimates of brood-rearing habitat: priority habitat and high priority habitat. The selected Kappa threshold for 2014 and 2015 was 0.32. Based on this statistic, the area of priority brood-rearing habitat in 2014 was 2,154,137.5 ha (Figure 1.8) and in 2015 was 636,493.75 ha (Figure 1.11), all within the Kansas portion of the lesser prairie-chicken range. The selected sensitivity-specificity sum maximizer threshold for 2014 and 2015 was 0.52. Based on this threshold, the area of high priority brood-rearing habitat in 2014 was 8,225 ha (Figure 1.9) and in 2015 was 3,993.75 ha (Figure 1.12). Based on estimates from the Kappa statistic, priority habitat area decreased by 70.45% from 2014 to 2015. Based on estimates from the sensitivity-specificity sum maximizer statistic, high priority habitat area decreased by 51.44% from 2014 to 2015.

Accuracy in the brood random forest model was determined by the percent correctly classified (PCC), the sensitivity (defined as the percent of presences correctly classified; Cutler et al. 2007), and the specificity (defined as the percentage of absences correctly classified; Cutler et al. 2007). The PCC of the brood random forest model was 97.73%, the sensitivity was 96.9%, and the specificity was 98.14%, all indicating good model fit.

Discussion

Through the use of NDVI and 9 NDVI-based vegetation phenology metrics, I demonstrated that yearly averaged vegetation phenology metrics at multiple spatial scales can be used to predict nest- and brood-site selection. However, NDVI phenology metrics may be more useful for predicting brood rearing habitat. Five of the 9 vegetation phenology metrics can be useful in the prediction of brood-rearing habitat abundance within the Kansas portion of the lesser prairie-chicken range, particularly when used in a model with gradient landscape variables.

Nest-site Selection

Originally, I predicted a quadratic relationship between snapshot NDVI and nest site-selection, with probability of use optimized in the 0.3-0.4 range, but was unable to confirm this prediction. One characteristic of a lesser prairie-chicken nest site is the presence of both living and residual cover (Lautenbach et al. 2019). Given that NDVI only detects living vegetation and that nesting tends to begin before all vegetation is out of dormancy, I expected NDVI values in the 0.3-0.4 range to capture optimal conditions at a nest site, particularly regarding the presence of living and residual cover. Snapshot NDVI does not appear to be related to nest-site selection at a 30 m pixel resolution, suggesting that females do not select sites based on greenness at the time of laying, but select sites based on the structure and density of residual vegetation.

It is possible that finer scale imagery could improve nest-site selection predictions. Privately owned satellites and other airborne sensors offer satellite imagery at <1 m pixel resolution and capture greater detail within a pixel. These finer scales images may capture more information regarding greenness conditions and how they relate to vegetation structure at the nest site and may yield different results. For example, aerial imagery collected at a 5- and 10-cm pixel resolution revealed that specific lesser prairie-chicken nest-site characteristics (100% VOR, 50% VOR, 25% VOR, point center tallest vegetation, among others) in western Kansas were significantly different compared to random sites, making it possible to remotely model nesting habitat at that scale (Price et al. 2015).

Alternatively, the limited utility of Snapshot Landsat 8 imagery in my study may be due to the simple fact that my calculated measures of NDVI are a snapshot at one point in time. In all likelihood, individuals are selecting nest sites based on numerous physical characteristics which may be better represented by season-long productivity measures. Vegetation phenology metrics, however, tell a different story.

Where snapshot NDVI measures NDVI at one point in time, NDVI-based vegetation phenology metrics quantify patterns in greenness throughout the growing season, including the times at which phenological events occur. Originally, I predicted that nest-site selection would be best informed by a quadratic relationship with AMP, with probability of use optimized in the 0.3-0.4 range. The basis for my prediction was based on the presence of living and residual cover at nest sites. I was unable to confirm this prediction, and instead I documented greater probability of nest site-selection in grasslands with greater TIN. Time Integrated NDVI is the cumulative measure of productivity from the beginning of the growing season to the end of the growing season and is typically used as a proxy for density of green cover (i.e., net primary productivity; Tucker and Sellers 1986, Eklundh and Olsson 2003, Potter 2020, Potter and Alexander 2020). Within a 4-m area, female lesser prairie-chickens typically select nest sites with vegetation having less bare ground, greater visual obstruction (typically between 2.0 and 3.5 dm at 75% visual obstruction), and greater litter cover compared to what is available at random sites (Riley et al. 1992, Giesen 1994, Pitman et al. 2005, Patten and Kelly 2010, Lyons et al. 2011, Hagen et al. 2013, Fritts et al. 2016, Grisham et al. 2016, Lautenbach et al. 2019). Additionally, individuals within the Short-Grass Prairie/CRP Mosaic and Mixed-Grass Prairie ecoregions typically select nest sites with greater percentages of grass cover compared to shrub cover (Hagen et al. 2013, Grisham et al. 2014, Lautenbach et al. 2019). Visual obstruction, grass cover, and taller vegetation all contribute to the density of vegetation around the nest site and, by extension, the degree of concealment that benefit female reproductive efforts (Hagen et al. 2009, Hagen et al. 2013, Larsson et al. 2013, Dahlgren et al. 2016). Additionally, that the 250-m pixel scale is informative indicates that the density of vegetation 250 m around the nest is also important and does align with the mean daily displacements of females during the nesting season (173.9 m at the Clark study site, 204 m at the Red Hills study site, and 300 m at the Northwest study site; Verheijen et al. 2021). Overall, females typically select nest sites containing denser vegetation compared to what is available at random sites, as TIN can be correlated with herbaceous cover and visual obstruction (Chapter 3). The relationship between TIN and nest sites is also evident in phenological comparisons between successful and unsuccessful nest sites, with successful nest sites having greater TIN compared to unsuccessful nest sites (Chapter 2). Ultimately, the 250-m eMODIS phenology metrics, specifically TIN, have utility in predicting nest-site selection, as they appear to reinforce the importance of greater vegetation cover at sites used for nesting by lesser prairie-chickens.

Brood site-selection

Brood-site selection was influenced by Amplitude (AMP) at the 370-m scale and varied across years. Amplitude measures productivity across the growing season as the difference between NDVI at the start of the growing season (SOSN) and NDVI at the peak of the growing season (MAXN; USGS 2021e). Greater AMP values at 370 m around brood sites indicated accelerated rates of productivity at brood sites compared to what was available. Notably, the informative 370 m scale aligns with daily displacement distances of brooding lesser prairie-chickens that ranged from 99.4-372 m (Verheijen et al. 2020). Lesser prairie-chickens are vulnerable in the weeks following hatch and cannot fly or walk the same distances that an adult can. Thus, movement tends to be more restricted during this time and resources need to be available in a smaller area for the brood and female to access them (Sullins et al. 2018a, Verheijen et al. 2020). Such resources include arthropods and forbs, two critically important food sources for chicks (Savory 1989, Sullins et al. 2018a). Abundances and biomass of these resources have been linked to grassland productivity (Siemann 1995, Perner et al. 2005, Fernández-Tizón et al. 2020, Lu et al. 2020, Traba et al. 2022). The importance of AMP at the 370-m scale confirms the importance of resource needs that are likely supplied by greater grassland productivity at this scale.

Additionally, probability of brood use in relation to AMP differed across years, though differences between years were not statistically significant. Notably, the relationship between AMP and probability of use was much stronger in 2015. Observed differences in yearly probability of use may be due to the high variability of grassland phenology due to precipitation, diverse grazing regimes, temperature, etc. (Reed et al. 1994). For example, within the study areas, growing season precipitation was greater in 2015 compared to 2013 and 2014. Conditions in 2013 were particularly dry in western Kansas, with precipitation returning to relatively normal amounts in 2014 and 2015 (Sullins et al. 2018b, Plumb et al. 2019, Lautenbach et al. 2019). Additionally, grazing pressure was significantly lower in 2015 compared to 2013 and 2014 (D. S. Sullins, Kansas State University, personal communication). Given the interannual differences in grazing and precipitation, yearly differences in AMP and probability of use were likely normal responses and reflective of within-year variations of extrinsic factors within study sites. Overall, AMP at the 370-m scale remains informative across years, though interannual variability may limit the availability of these important productivity conditions.

Predicting reproductive habitat abundance

Brood Habitat

The presence of phenology metrics in my random forest model provided a finer-scale estimation of within grassland brood-rearing habitat in Kansas compared to prior species distribution models that only used grassland composition and anthropogenic features as predictors. My models revealed that the availability of reproductive habitat within grasslands is limited and variable between years. Sullins et al. (2019) used a random forest model to predict lesser prairie-chicken occurrence within the Kansas and Colorado portion of their occupied range. Predictors in Sullins et al. (2019) were related to anthropogenic features and gradient landscape variables, such as percent grassland at multiple scales. Results from this model identified large tracts of grasslands with minimal anthropogenic features that may be available to lesser prairie-chickens, but it was unclear how much of those grasslands were potential lesser prairie-chicken habitat. My study builds on this previous research, and hierarchically identifies areas within those grasslands where probability of use is high, moderate, or low, based on phenology metrics and landscape variables.

The top 3 variables of importance in the 2014 and 2015 brood random forest model were EOST at the 1-km scale, AMP at the 370-m scale, and TIN at the 1-km scale. The most important variable, EOST, describes the date at which the end of the growing season occurred. This indicates that females with broods were using sites that remain greener and more productive for a longer period compared to what was available. Brood-rearing females have been observed moving their broods to more productive areas as the growing season progresses, such as into wetter areas (D. S. Sullins and D. A. Haukos, Kansas State University, personal communication).

Chicks have high caloric needs during the brood-rearing period, and the brood-rearing female needs to meet her own energy needs as well. Areas that remain productive for longer periods of time are likely able to provide females and their broods with resources later into the brood-rearing season, meeting their needs for a longer period of time. This also relates to NDVI at the end of the growing season (EOSN), though EOSN carries less importance compared to EOST. Other grouse are known to select for wetter locations during brood-rearing. Brood-rearing greater sage-grouse (*Centrocercus urophasianus*) will use riparian areas more frequently as broods age, allowing them to take advantage of late-growing season food sources (Danvir 2002, Crawford et al. 2004, Dzialak et al. 2011, Dinkins et al. 2014). Females with younger broods are less likely to use riparian areas, and in fact tend to nest farther away from riparian areas (Dinkins et al. 2014). Use of riparian areas by late-stage sage-grouse broods is similar to what has anecdotally been observed for lesser prairie-chickens.

Although EOST was the most influential variable in this model, AMP at the 370 m scale and TIN at the 1 km scale had similar influence, both of which measure productivity across the growing season rather than index the end of the growing season as EOST does. Specifically, AMP measures the difference between NDVI at the start of the growing season and NDVI at the peak of the growing season (otherwise known as MAXN; USGS 2021e). Greater values of AMP indicate greater increases in productivity and greenness, whereas low values of AMP indicate a lack of growing vegetation. For example, an AMP value of 0.1 would represent minimal growth or green-up of vegetation, potentially due to a pixel containing a greater proportion of bare ground or residual vegetation that is not measured by NDVI. In my random forest model, probability of use increased with greater AMP values, which would point to increased overall greenness and productivity at brood sites within grasslands compared to what was available.

Additionally, and as discussed earlier, I expect greater values of AMP to reflect greater food abundance at brood sites, particularly arthropods. Arthropods are a crucially important component of brood diet, and plant productivity, structure, and greater values of NDVI have been shown to influence arthropod abundance and biomass (Dennis et al. 1998, Harrison et al. 2018, Fernández-Tizón et al. 2020). The TIN metric, also a season-long metric, measures cumulative integrated photosynthetic activity across the growing season and is often used as a proxy for the density of vegetation cover (Potter 2020, Potter and Alexander 2020) and biomass production (Goward et al. 1985, Tieszen et al. 1997, Wang et al. 2008, Rigge et al. 2013). Here, and similar to my nest-site selection analyses (this chapter), probability of use increased with increasing TIN measures. Low TIN values would relate to low cumulative photosynthetic activity across the growing season, and therefore, relatively less cover or biomass. Larger values of TIN likely reflected greater cover at brood sites, which is important for brood concealment. Although the most important variables in my model were related to phenology metrics, landscape variables still carried importance in this model.

My results are consistent with other published work related to resource selection of grassland-dominated landscapes and avoidance of anthropogenic features (Behney et al. 2012, Pitman et al. 2010, Sullins et al. 2019, Plumb et al. 2019). The fourth ranked variable of importance in my random forest model was percent grassland within 5 km. Probability of use peaked around 77%-80%, which is consistent with Sullins et al. (2019) and further stresses the importance of available grassland dominated landscapes for lesser prairie-chicken persistence. Additionally, though these variables carried low importance, density of oil wells and density of transmission lines within 2 km exhibited similar patterns of use, where low densities of oil wells and transmission lines resulted in greater probabilities of use. Lesser prairie-chickens tend to avoid tall vertical structures due to perceived predation risks. My results further indicated that the number of anthropogenic features on the landscape needs to remain low at broader scales to facilitate use by lesser prairie-chickens.

Last, I observed an unexpected non-linear relationship with density of county roads. Probability of use increased as the number of county roads increased, peaked at approximately 40 county roads within 2 km, and decreased before leveling out past 60/km. This appears to indicate that moderate numbers of county roads may not negatively affect predicted use by lesser prairie-chickens, which has similarly been observed by Tanner et al. (2020) and, to a lesser degree, Sullins et al. (2019). Additionally, although I have no data regarding traffic on unpaved county roads at any of our study sites, I expect traffic to be light on these roads, which may contribute to this unexpected relationship. It is important to remember that these results may have been different if random locations had been distributed among all cover types found within the study areas. All random locations used in my research were located exclusively within grasslands used by lesser prairie-chickens, which might limit the utility of these predictors that are likely still important at broader scales as Sullins et al. (2019) would suggest.

Although phenology metrics and gradient landscape variables were important in predicting brood-rearing habitat availability, my random forest model revealed that the abundance of brood-rearing habitat within grasslands is limited in Kansas and variable between years. I observed a decline in overall potential habitat from 2014 to 2015 in Kansas. Reasons for this decrease remain unclear, but again may be due to differences in precipitation or land use. The ~50% decrease in high priority brooding habitat between years stresses the importance of sustainably managing grasslands as well as focusing targeted management and monitoring within priority grasslands. It is abundantly clear that when productivity measures are taken into consideration, large tracts of intact priority grasslands for brood rearing are nearly non-existent, making conservation efforts on what remains critically important (Gehrt et al. 2020).

Notably, there were no high priority grasslands identified within the Northwest study site in both 2014 and 2015, nor within the northwestern extent of the lesser prairie-chicken range in Kansas, despite the presence of CRP grasslands in this ecoregion (Short-grass Prairie/CRP Mosaic Ecoregion). By definition, grasses in this ecoregion are shorter and tend to lack adequate structure for lesser prairie-chicken use (Hagen et al. 2004, van Pelt et al. 2013, Haukos and Zavaleta 2016, Dahlgren et al. 2016), though implementation of CRP mitigates some of these issues (Fields 2004, Dahlgren et al. 2016). Although the presence of CRP grasslands is overall beneficial in this ecoregion, particularly during the nesting season, CRP can be too dense for lesser prairie-chicken chicks to navigate, which can result in decreased use during the brood-rearing season (Dahlgren et al. 2016). Similarly, although somewhat rarely, females in this ecoregion have been observed to take their broods into crop fields for forage, particularly later in the growing season (Fields 2004, Fields et al. 2006), which is a cover type that we did not evaluate in this study. As such, the role that crop fields play in estimating potential habitat will need to be evaluated further.

Based on estimates from using the Kappa Statistic as a threshold, I identified priority brood habitat in the southwest corner of Gove County and the southeast corner of Logan County, which were identified as grassland-dominated landscapes with minimal anthropogenic features in Sullins et al. (2019) and important habitat for lesser prairie-chickens. That my estimates are similar despite the addition of phenology variables in my model further supports targeted conservation in these areas. Of the overall predicted potential habitat in Kansas based on landscape variables alone in Sullins et al. (2019), only 1.64% was predicted as brood-rearing habitat in 2014, all of which was predicted in the mixed-grass prairie within and adjacent to the Clark study site. In 2015, only 0.8% of the total estimated habitat abundance was predicted as brood-rearing habitat, as area of high priority habitat declined 51.4% from 2014 to 2015, providing strong evidence that the availability of brood-rearing habitat may be limited within Kansas, especially when compared to total estimated habitat availability by Sullins et al. (2019).

The importance of understanding reproductive habitat availability for lesser prairie-chickens cannot be understated. Lesser prairie-chicken populations continue to decline, and whether or not this species will persist over the next 25 years is questionable throughout much of the current occupied range (USFWS 2021). Reproductive parameters such as nest, brood, and juvenile survival have been identified as limiting factors for lesser prairie-chickens (Pitman et al. 2006, Hagen et al. 2009, Ross et al. 2018), which further enforces the idea that priority reproductive habitat needs to be protected or managed in a way that maintains productivity requirements and keeps anthropogenic densities low in the hopes that nests and broods are successful and survive to the juvenile stage (Hagen et al. 2005, Pitman et al. 2006, Ross et al. 2018, Plumb et al. 2019). Albeit productivity and low anthropogenic feature densities alone are not going to ensure the development of broods to juveniles, the fact remains that current management practices need to advance if lesser prairie-chicken populations are to persist. The identification and protection of priority habitat is a step in the right direction.

Nest Habitat

Efforts to use phenology metrics and gradient landscape variables to predict potential nesting habitat in Kansas were ultimately unsuccessful. One notable pattern was that TIN at the 1-km scale was the most important variable in my random forest model, which is somewhat consistent with the relationship that was observed in my nest-site selection analyses, with TIN at the 250-m scale predicting use. This further supports the idea that TIN may be capturing density of cover around nest sites, but the weak relationship may indicate that other characteristics are more important than the productivity of grass around nest sites as represented by phenology metrics.

Conclusions

I have provided evidence that vegetation phenology metrics and gradient landscape variables are useful in the prediction of nest- and brood-site selection and the combination of phenology metrics and landscape variables can be used to predict brood habitat abundance in Kansas. Although I was unable to link 30-m Snapshot NDVI measures to nest-site selection, it remains clear that specific phenology metrics are capturing structure and canopy cover of vegetation at the 250-m scale, as well as at additional scales around used sites. Ultimately, I demonstrated that habitat selection not only manifests at fine microhabitat scales, but at broader spatial scales as well.

Further, an alarming lack of priority grasslands were predicted in the Kansas portion of the lesser prairie-chicken range. Given the uncertainty surrounding the viability of this species over the next 25 years, measures need to be taken to preserve and sustainably manage identified priority areas, which may be most effective through the use of partnerships and financial incentives, such as conservation easements (Augustine et al. 2019). Additionally, given that the Short-Grass Prairie/CRP Mosaic Ecoregion supports the largest abundance of lesser prairie-chickens, conservation efforts should be focused in areas where the greatest amount of potential habitat was identified by the Kappa statistic, as no high priority habitat was predicted here.

Overall, Kansas is a critically important stronghold for lesser prairie-chickens as it encompasses large portions of the mixed-grass, short-grass, and sand sagebrush prairies, which together support 92% of the range-wide lesser prairie-chicken population (Nasman et al. 2022). To prevent further population declines, conservation of grassland dominated landscapes that meet specific productivity requirements and have minimal anthropogenic features is needed.

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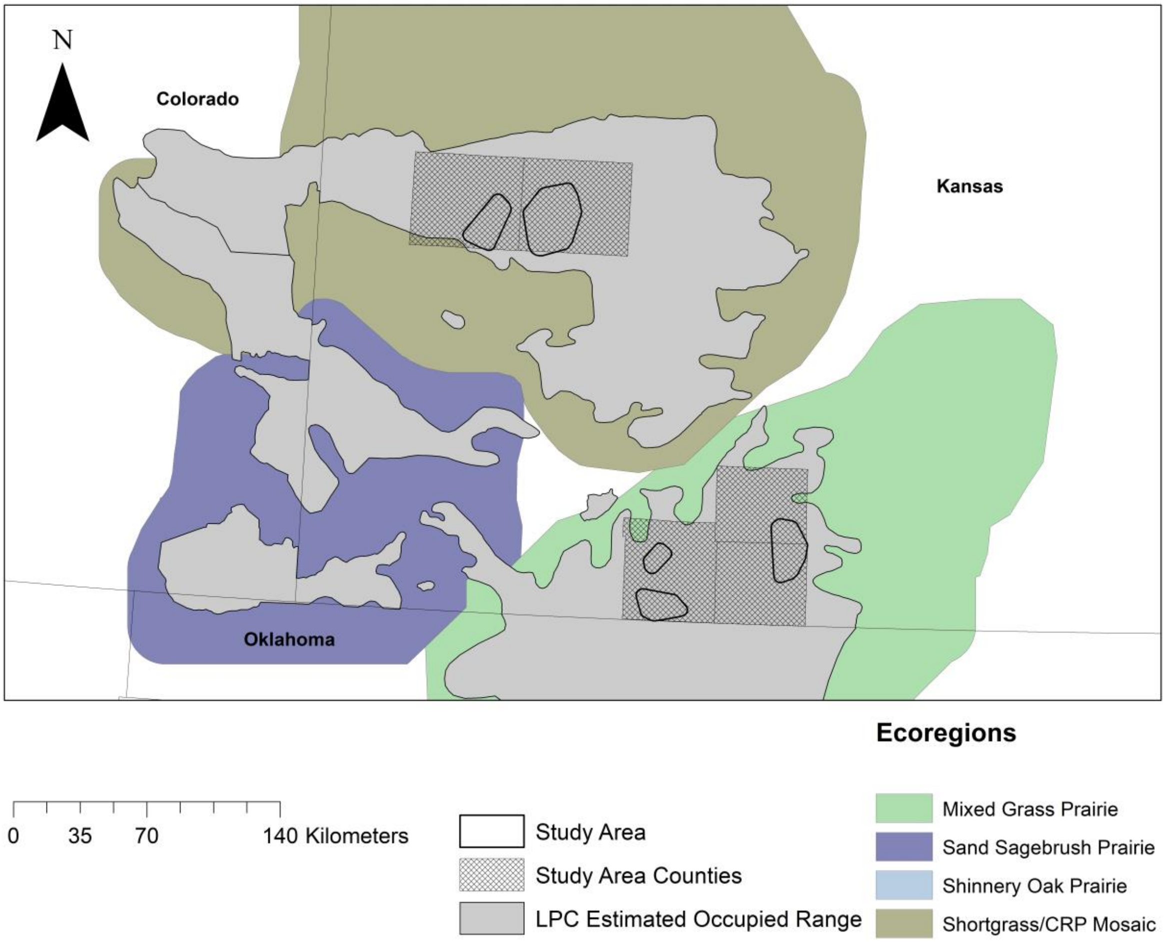

Figure 1.1. Map of the study area (Red Hills, Northwest, and Clark) covering Logan, Gove, Clark, Kiowa, and Comanche counties. Study areas are located within the Mixed-Grass and Short-Grass/Conservation Reserve Program (CRP) Mosaic of the lesser prairie-chicken range in western Kansas.

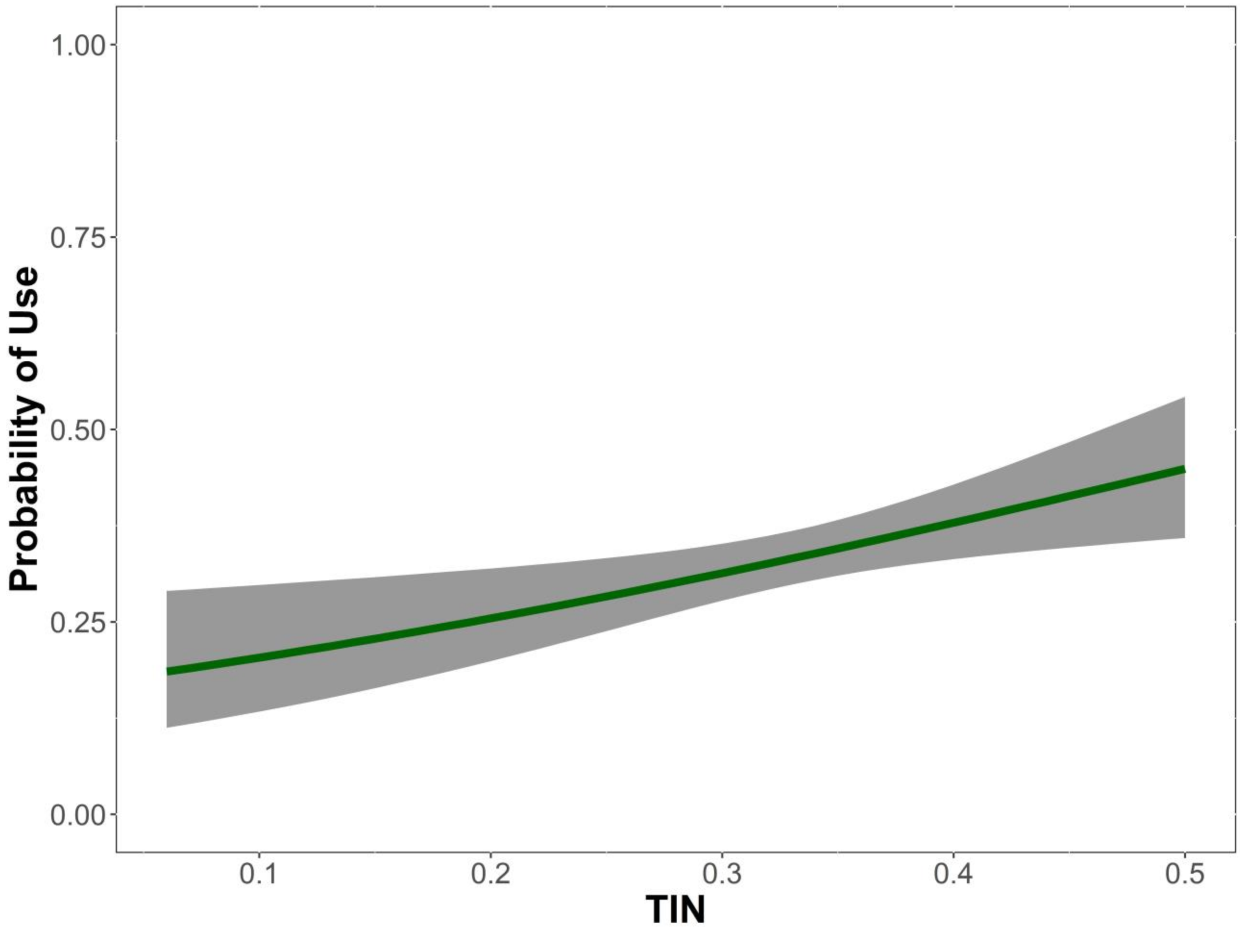

Figure 1.2. Probability of use (nest site-selection) as a function of the remotely sensed phenology metric Time Integrated NDVI (TIN) at the 250-m pixel scale. Values of TIN were extracted from C6 AQUA MODIS Remote Sensing Phenology (RSP) images, downloaded from https://phenology.cr.usgs.gov/viewer/. TIN represents the cumulative integrated photosynthetic activity across the growing season. Nest data was collected from 2013-2015 in Clark, Kiowa, Comanche, Logan, and Gove counties in western Kansas. The shaded grey area depicts 95% confidence intervals.

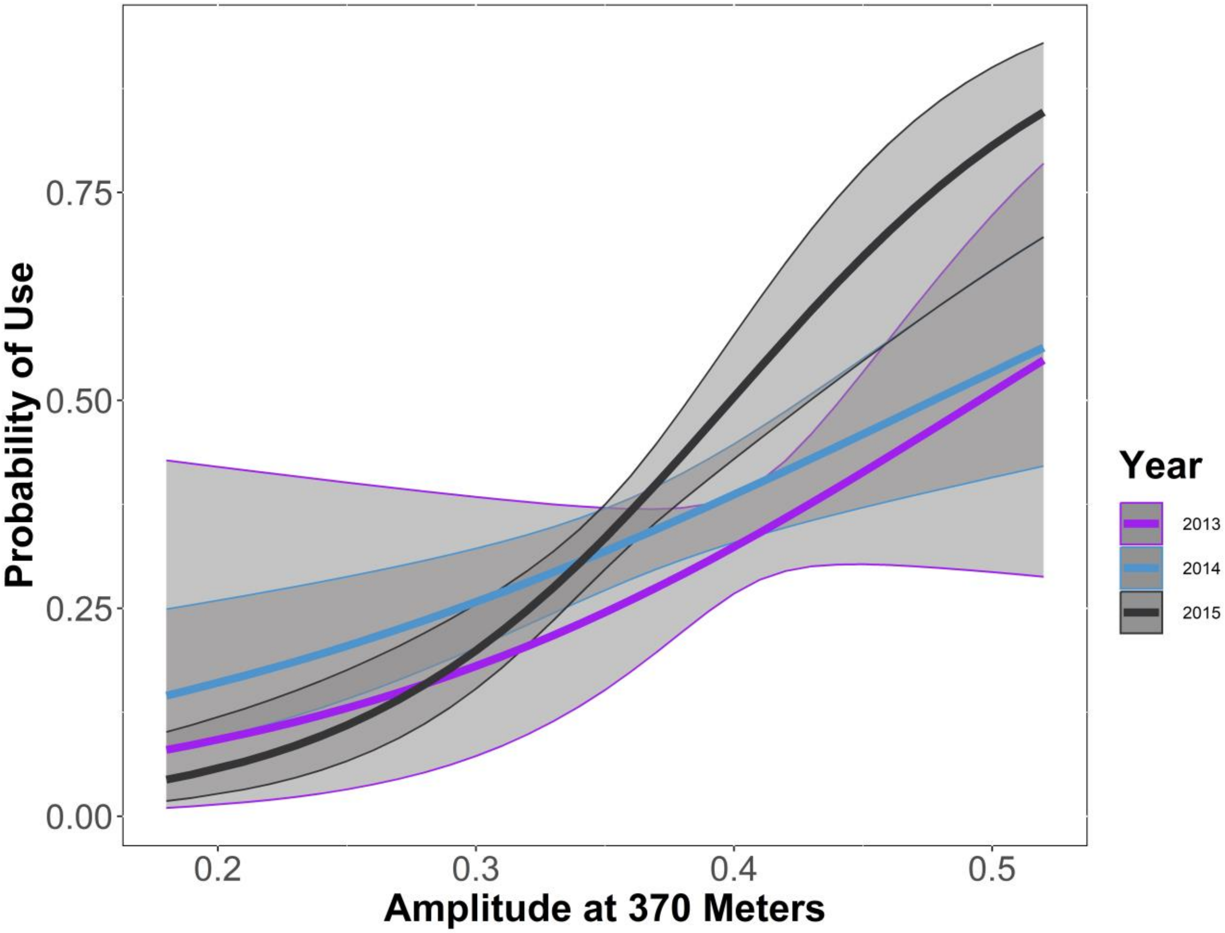

Figure 1.3. Probability of female brood-rearing lesser prairie-chicken use as a function of Amplitude at the 370-m scale and Year. Amplitude values were extracted from C6 AQUA MODIS Remote Sensing Phenology (RSP) images. Brood locations are from Clark, Kiowa, Comanche, Gove, and Logan counties in Western Kansas in 2013, 2014, and 2015. The shaded grey areas represent 95% confidence intervals.

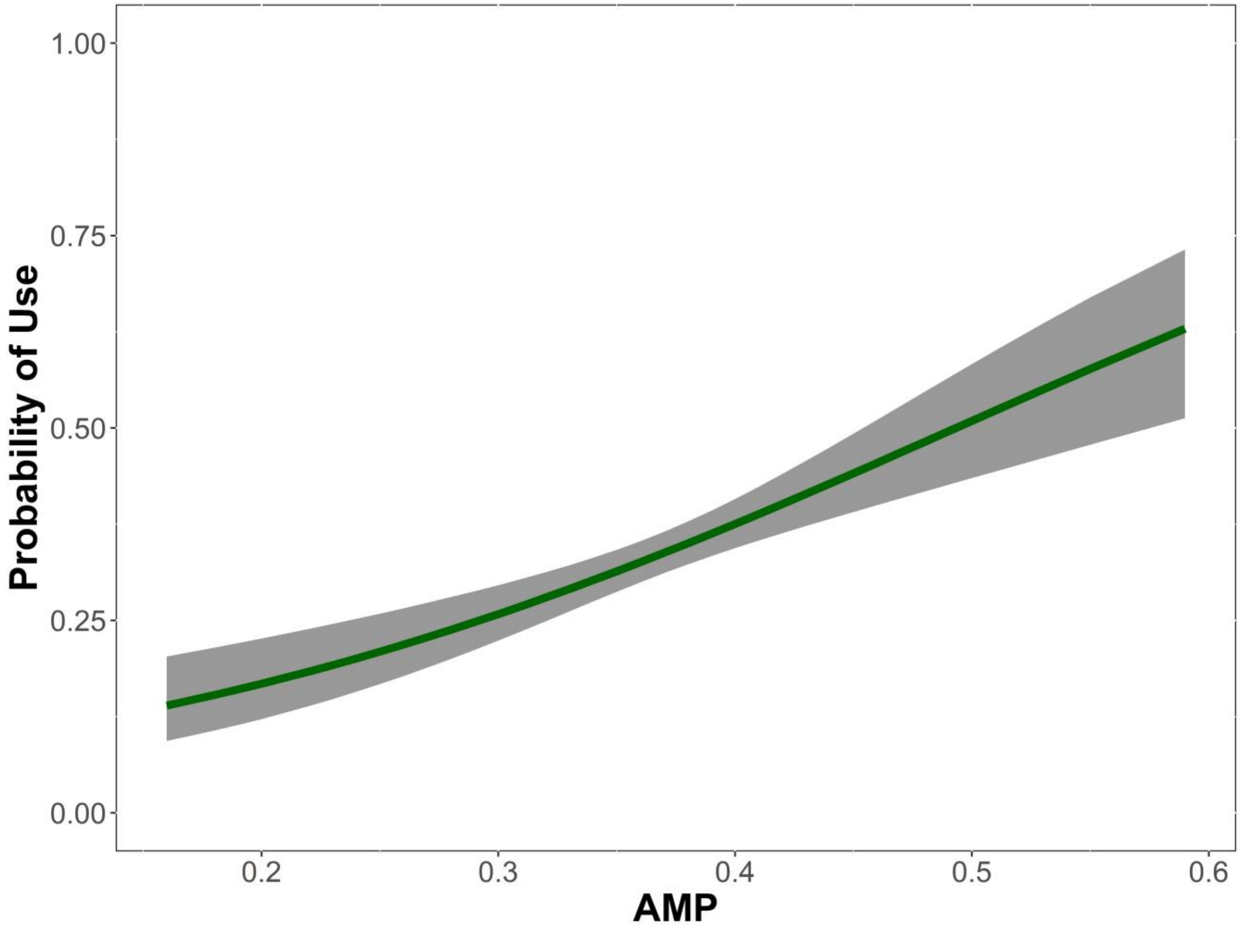

Figure 1.4. Probability of female brood-rearing lesser prairie-chicken use as a function of Amplitude at the 250-m pixel scale. Amplitude values were extracted from C6 AQUA MODIS Remote Sensing Phenology (RSP) images. Brood locations are from Clark, Kiowa, Comanche, Gove, and Logan counties in Western Kansas in 2013, 2014, and 2015. The shaded grey areas represent 95% confidence intervals.

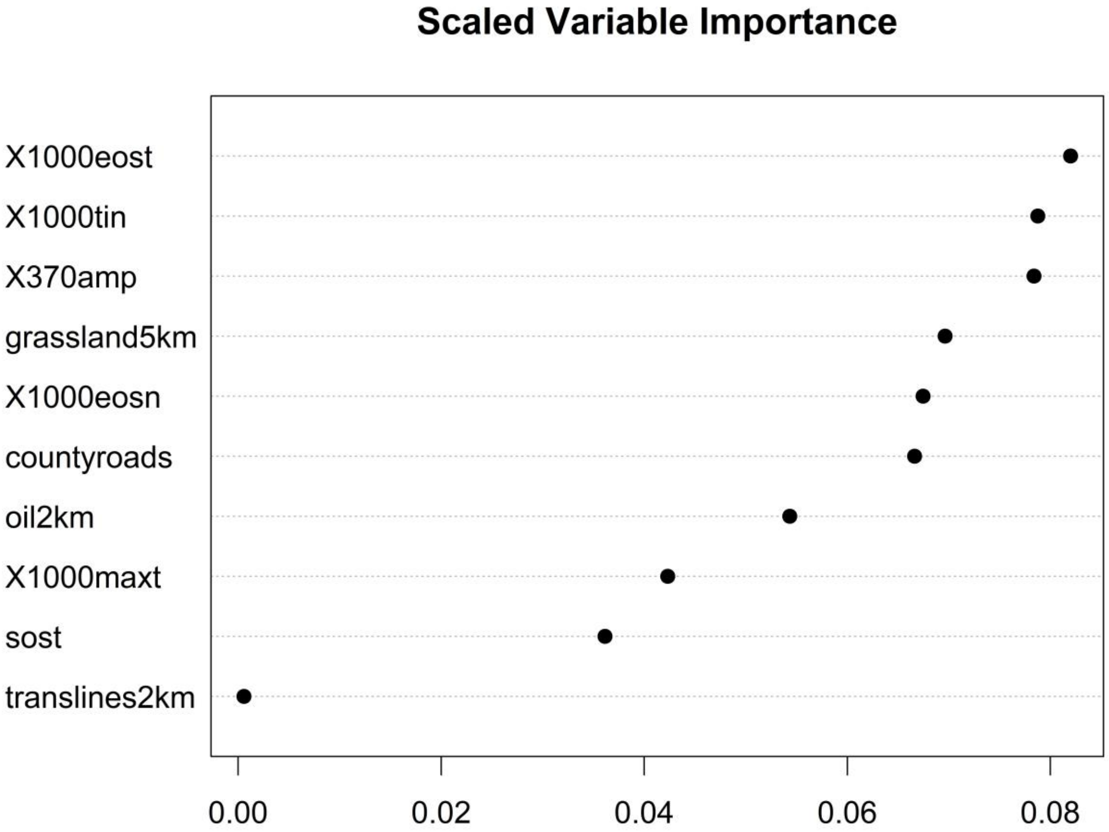

Figure 1.5. The scaled variable importance values of the 10 variables (a combination of gradient landscape variables and NDVI-based vegetation phenology metrics) used in the 2014 and 2015 random forest models predicting brood habitat abundance in western Kansas. Variables in this plot are listed, from top to bottom, in order of most important to least important.

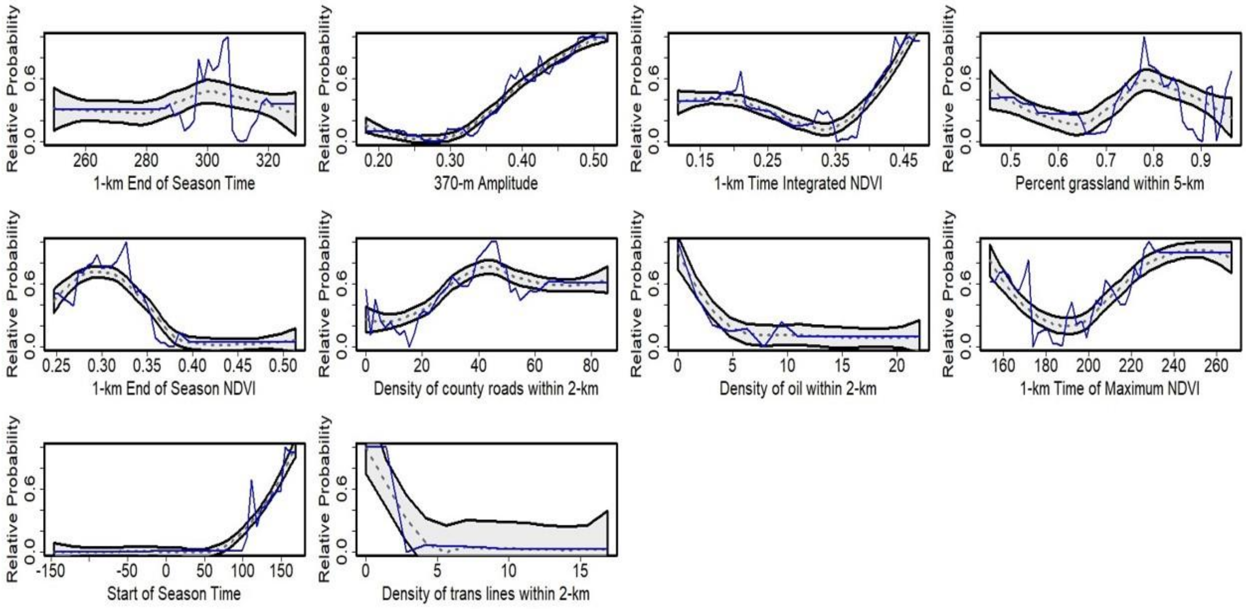

Figure 1.6. Partial dependency plots for all 10 variables (consisting of gradient landscape variables and NDVI-based vegetation phenology metrics) used to predict brood-rearing habitat abundance in western Kansas based on brood location data from 2014-2015. The partial dependency plots depict relative probability of use. Raw estimates of probability of use are shown by the blue line, and the shaded grey area is 95% confidence intervals. The dashed grey line depicts a loess polynomial regression and smooths the raw probability of use estimates.

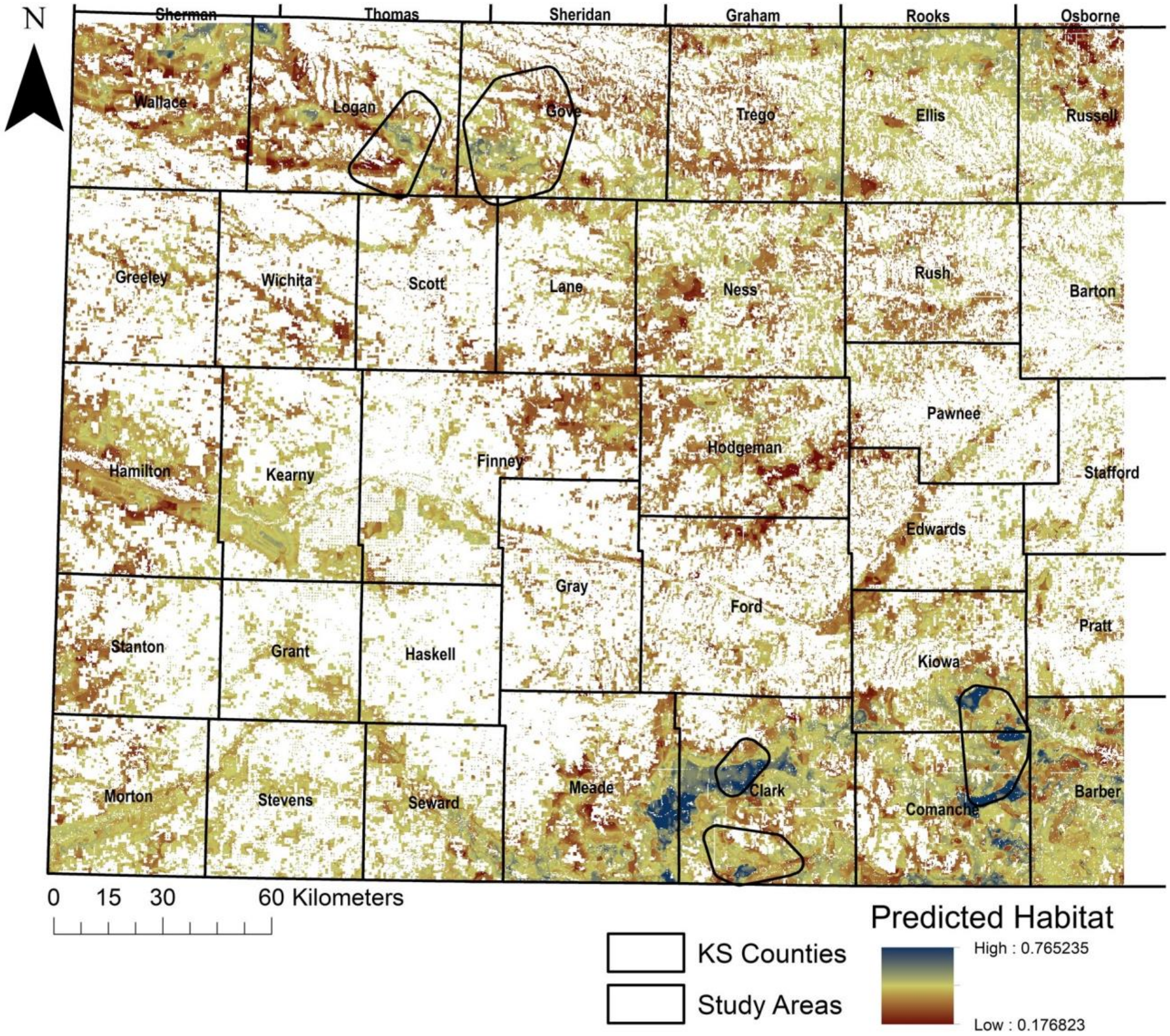

Figure 1.7. Predicted habitat surface from 2014 based on probability of use. Areas with low probability of use are depicted in deep reds, areas with moderate probabilities of use are depicted in deep greens, and areas of high probability of use are depicted in deep blues. Habitat abundance was estimated using a random forest approach exclusively within grasslands. All white space is non-grassland. The locations of the 3 study sites (Clark, Red Hills, and Northwest) are outlined in black and span 5 counties in western Kansas (Clark, Kiowa, Comanche, Logan, and Gove) where lesser prairie-chicken broods were monitored from 2013-2015. Logan and Gove counties make up the Northwest study site, Clark county makes up the Clark study site, and Kiowa and Comanche counties make up the Red Hills study site.

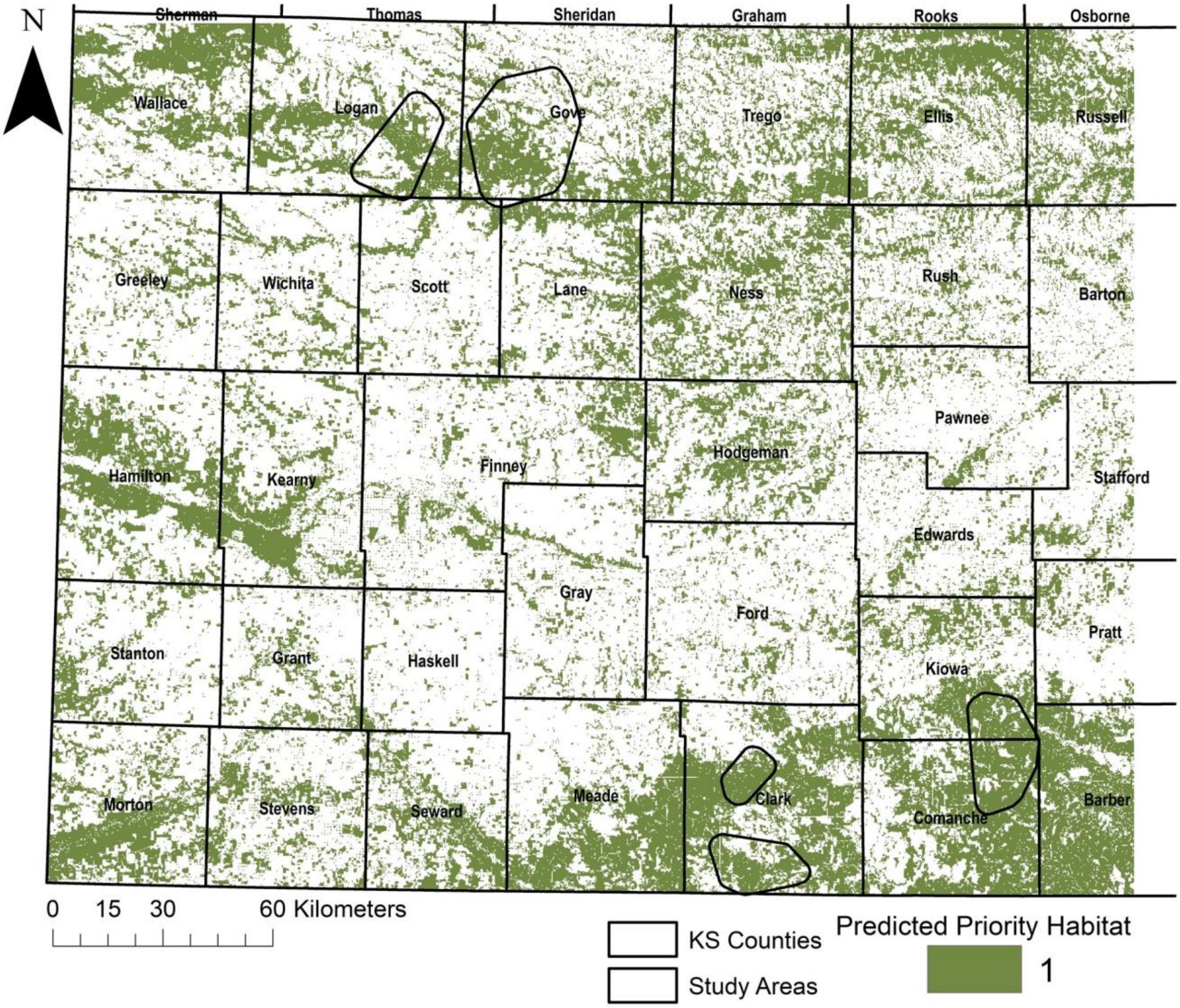

Figure 1.8. Predicted priority habitat in 2014. Areas in green represent estimated priority brood habitat abundance in 2014 in grasslands with minimal anthropogenic feature densities. Priority habitat abundance was estimated using a random forest approach and the Kappa threshold. Estimated abundance is based on probabilities of use > 0.32. The amount of estimated grasslands depicted in this figure is 2,154,137.5 ha. Locations of the three study sites are outlined in black (Clark, Red Hills, and Northwest) and spanned five counties in western Kansas (Clark, Kiowa, Comanche, Logan, and Gove) where lesser prairie-chicken broods were monitored from 2013-2015. Logan and Gove counties make up the Northwest study site, Clark county makes up the Clark study site, and Kiowa and Comanche counties make up the Red Hills study site.

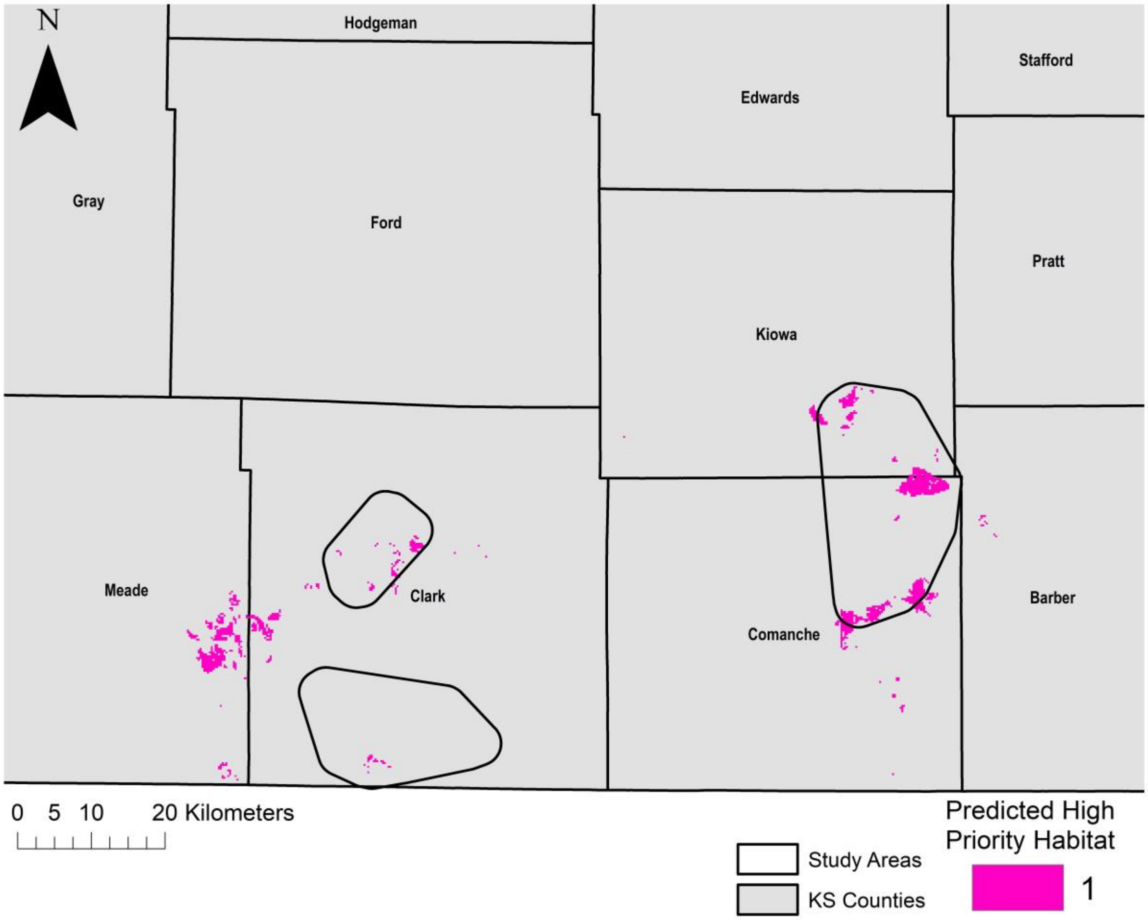

Figure 1.9. Predicted high priority habitat in 2014. High priority habitat abundance was estimated using a random forest approach and the sensitivity-specificity sum maximizer threshold. Estimated abundance is based on probabilities of use > 0.52. Areas in pink represent estimated high priority brood habitat abundance in 2014 in grasslands with minimal anthropogenic feature densities. The amount of estimated priority grasslands depicted in this figure is 8,225 ha. The locations of two of the three study sites (Clark and Red Hills) are outlined in black and span three counties in western Kansas (Clark, Kiowa, and Comanche) where lesser prairie-chicken broods were monitored from 2013-2015. Clark county makes up the Clark study site, and Kiowa and Comanche counties make up the Red Hills study site. The third study site, Northwest, is not depicted here due to a complete absence of priority grasslands predicted within this study area.

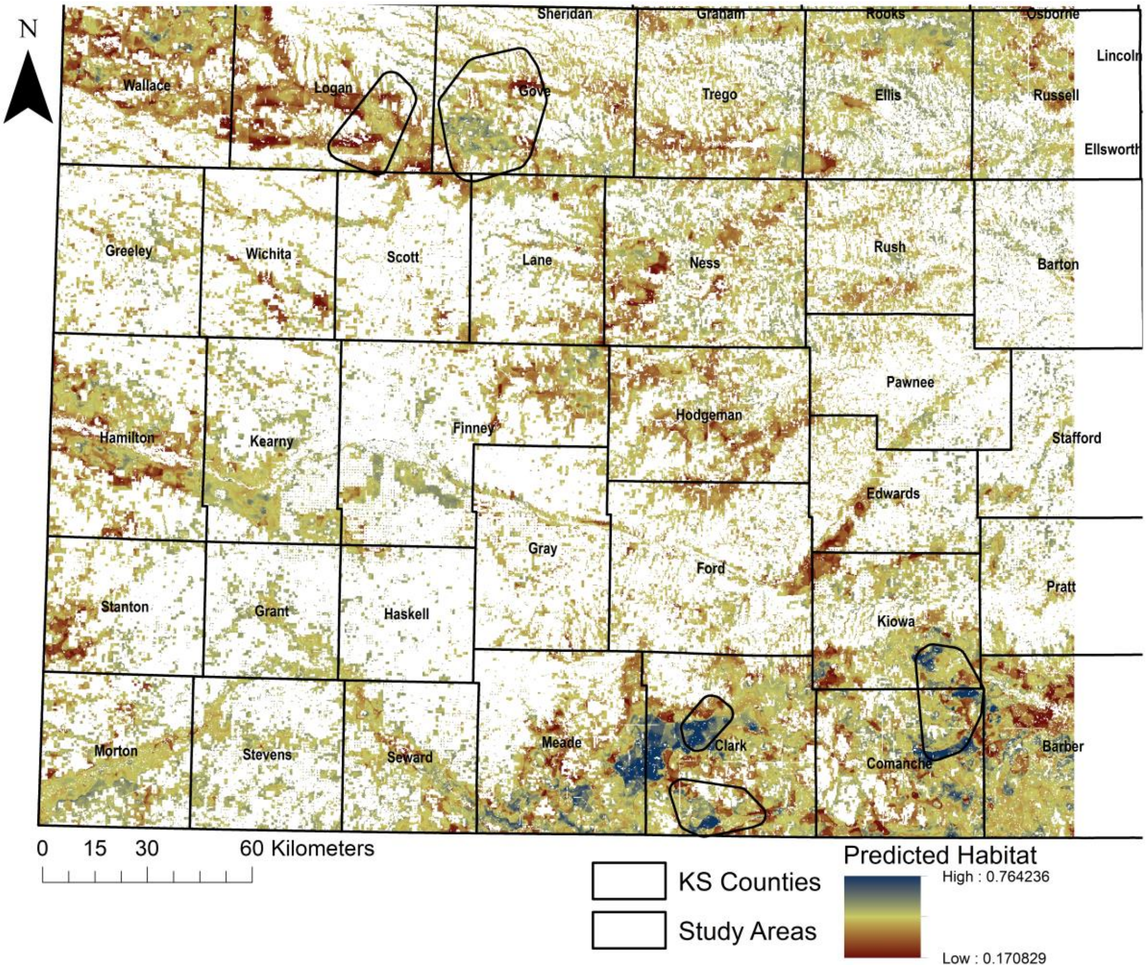

Figure 1.10. Predicted habitat surface from 2015 based on probability of use. Areas with low probability of use are depicted in deep reds, areas with moderate probabilities of use are depicted in deep greens, and areas of high probability of use are depicted in deep blues. Habitat abundance was estimated using a random forest approach exclusively within grasslands. All white space is non-grassland. Locations of the 3 study sites (Clark, Red Hills, and Northwest) are outlined in black and span 5 counties in Kansas (Clark, Kiowa, Comanche, Logan, and Gove) where lesser prairie-chicken broods were monitored from 2013-2015. Logan and Gove counties make up the Northwest study site, Clark county makes up the Clark study site, and Kiowa and Comanche counties make up the Red Hills study site.

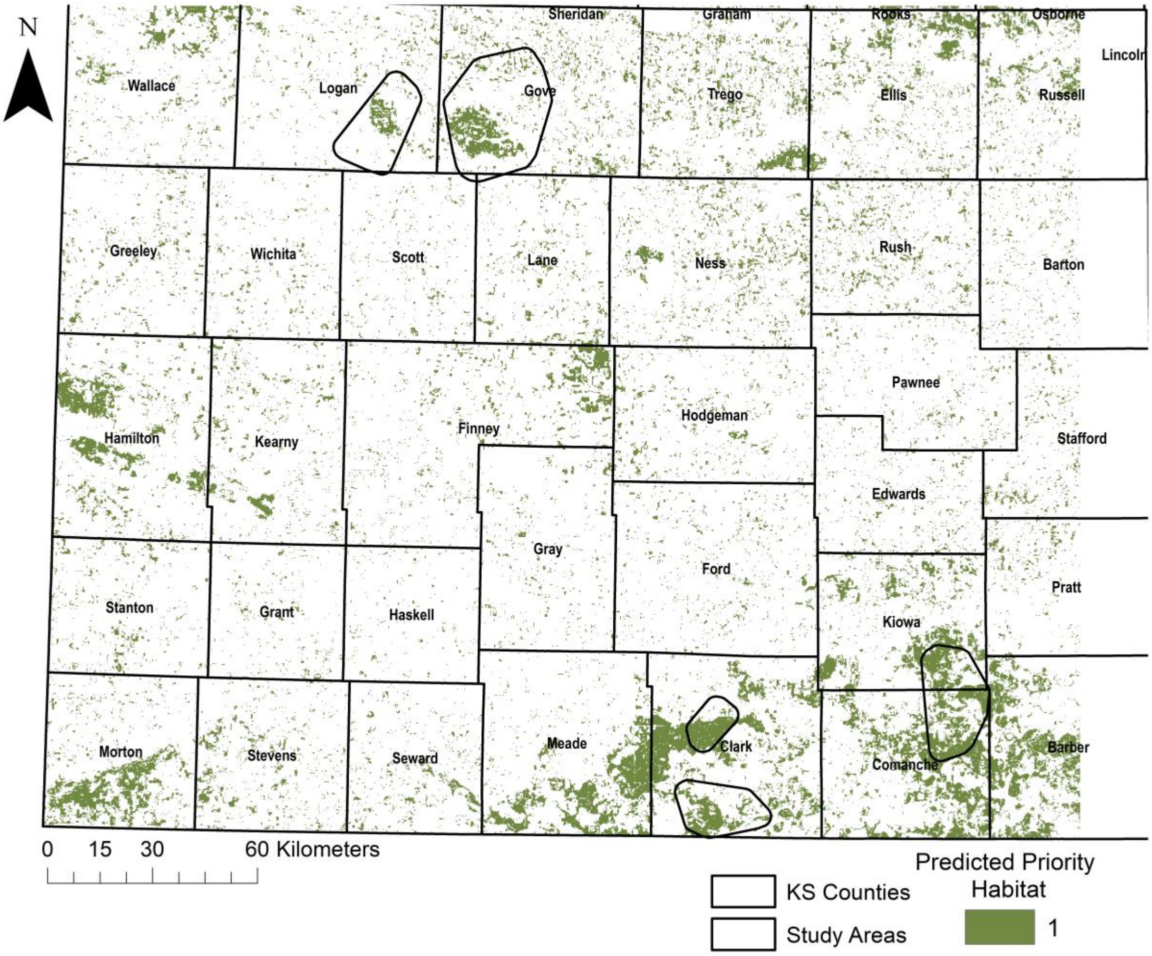

Figure 1.11. Predicted priority habitat in 2015. green represent estimated priority brood habitat abundance in 2014 in grasslands with minimal anthropogenic feature densities. Priority habitat abundance was estimated using a random forest approach and the Kappa threshold. Estimated abundance is based on probabilities of use > 0.32. Depicted in green, the amount of estimated priority grasslands depicted in this figure is 636,493.75 ha. The locations of the three study sites, outlined in black (Clark, Red Hills, and Northwest), spanned five counties in western Kansas (Clark, Kiowa, Comanche, Logan, and Gove) where lesser prairie-chicken broods were monitored from 2013-2015. Logan and Gove counties make up the Northwest study site, Clark county makes up the Clark study site, and Kiowa and Comanche counties make up the Red Hills study site.

Figure 1.12. **Predicted high priority habitat in 2015. High priority habitat abundance was estimated using a random forest approach and the sensitivity-specificity sum maximizer threshold. Estimated abundance is based on probabilities of use > 0.52. Areas in pink represent estimated high priority brood habitat abundance in 2015 in grasslands with minimal anthropogenic feature densities. The amount of estimated priority grasslands depicted in this figure is 3,993.75 ha. The locations of two of the three study sites (Clark and Red Hills), outlined in black, spanned three counties in western Kansas (Clark, Kiowa, and Comanche) where lesser prairie-chicken broods were monitored from 2013-2015. Clark county makes up the Clark study site, and Kiowa and Comanche counties make up the Red Hills study site. The third study site, Northwest, is not depicted here due to a complete absence of priority grasslands predicted within this study area.**

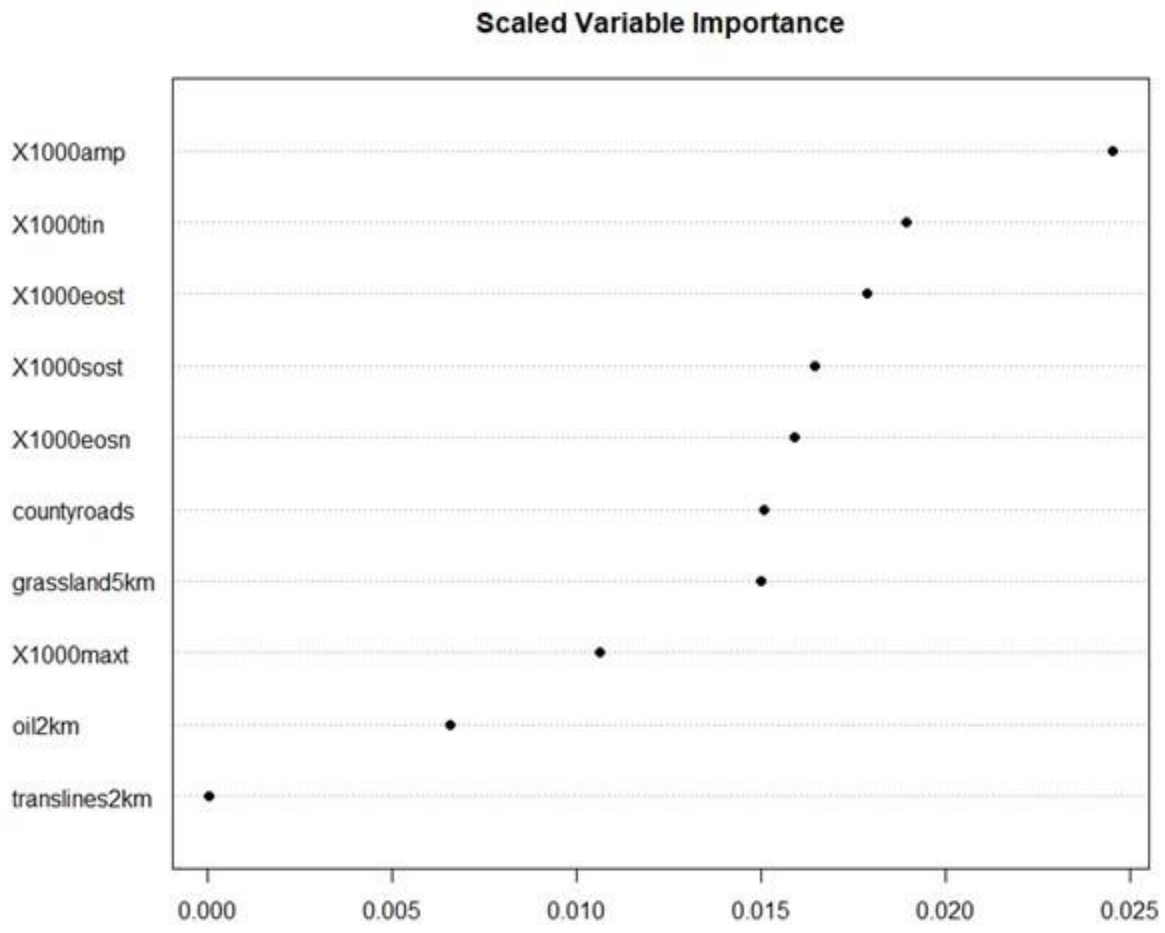

Figure 1.13. The scaled variable importance values of the 10 variables (a combination of gradient landscape variables and NDVI-based vegetation phenology metrics) used in the 2014 and 2015 random forest models predicting nest habitat abundance in western Kansas. Variables in this plot are listed, from top to bottom, in order of most important to least important.

Table 1.1. The 9 NDVI-based vegetation phenology metrics used in my analyses and their descriptions. All metrics are calculated and maintained by the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center. Each phenology metrics is calculated from weekly NDVI composites over a one-year period. Data is freely available from the USGS Phenology Viewer (https://phenology.cr.usgs.gov/viewer/).

Phenology Parameters	**Description**
SOST → Start of the growing season, time	Day of year at which a measurable photosynthetic increase takes place after senescence.
SOSN → Start of the growing season, NDVI	NDVI value of the first measurable photosynthetic increase after senescence.
EOST → End of the growing season, time	Day of year at which there is a measurable decline in photosynthetic activity.
EOSN → End of the growing season, NDVI	NDVI value on the day that there is a measurable downward trend in photosynthesis.
MAXN → Maximum NDVI	Highest level of photosynthetic activity detected in the growing season.
MAXT → Maximum NDVI, time	Day of year associated with the MAXN.
AMP → Amplitude	Difference between the SOSN and MAXN values.
DUR → Duration	Length of the growing season (i.e. the difference between the SOST and EOST).
TIN → Time Integrated NDVI	Cumulative integrated photosynthetic activity across the growing season.

Table 1.2. A priori candidate model set (n = 7) models used to model nest site-selection for lesser prairie-chickens at the Clark, Red Hills, and Northwest study sites from 2013-2015. Models tested include a null, a single variable snapshot NDVI (representing NDVI values at the time of nest initiation), snapshot NDVI with additive and interactive site and year variables, and a quadratic snapshot NDVI model.

Model	K[a]	ΔAICc[b]	AICc[c]	w_i[d]	Deviance[e]
Null	1	0.00	460.30	0.52	-229.15
Snapshot NDVI	2	1.74	462.04	0.22	-229.00
Quadratic snapshot NDVI	3	3.05	463.35	0.11	-228.64
NDVI + Year	3	3.63	463.93	0.08	-228.93
NDVI*Year	4	5.33	465.63	0.04	-228.76
NDVI + Site	4	5.61	465.91	0.03	-228.90
NDVI*Site	6	9.64	469.94	0.00	-228.85

[a] Number of parameters
[b] The difference in Akaike's Information Criterion adjusted for small samples size
[c] Akaike's Information Criterion adjusted for small sample size
[d] Akaike weights
[e] Deviance (-2*loglikelihood)

Table 1.3. 21 out of 48 *a priori* candidate models used to model nest site-selection for lesser prairie-chickens at the Clark, Red Hills, and Northwest study sites from 2013-2015. Models tested include single variable NDVI-based phenology metrics, single variable NDVI-based phenology metrics at multiple scales, multi-variable NDVI-based phenology metrics, additive and interactive site and year models, and a null model.

Model	K[a]	ΔAICc[b]	AICc[c]	w_i[d]	Deviance[e]
TIN	2	0.00	901.29	0.12	-448.64
TIN + AMP	3	1.04	902.33	0.07	-448.15
TINscale1	2	1.45	902.74	0.06	-449.36
TIN + Year	3	1.49	902.79	0.06	-448.38
TINscale2	2	1.71	903.00	0.05	-449.49
TIN*Year	4	1.76	903.05	0.05	-447.50
AMPscale2	2	1.79	903.08	0.05	-449.53
AMPscale3	2	1.82	903.11	0.05	-449.55
Quadratic TIN	3	2.02	903.31	0.04	-448.64
AMPscale3 + TINscale3	3	2.05	903.34	0.04	-448.65
TINscale3	2	2.37	903.66	0.04	-449.82
TINscale3 + SOSTscale3	3	2.77	904.06	0.03	-449.02
AMPscale1	2	2.95	904.24	0.03	-450.11
TIN*AMP	4	3.06	904.35	0.03	-448.15
AMP	2	3.09	904.38	0.03	-450.18
AMPscale3*TINscale3	4	3.10	904.39	0.03	-448.17
Quadratic AMP	3	3.23	904.52	0.02	-449.24
Quadratic TINscale1	3	3.45	904.74	0.02	-449.35
TINscale3 + AMPscale3 + SOSTscale3	4	3.56	904.85	0.02	-448.40
Quadratic AMPscale2	3	3.66	904.95	0.02	-449.46
Null	1	5.84	907.13	0.01	-452.56

Table 1.4. 21 out of 38 *a priori* candidate models used to model brood site-selection for lesser prairie-chickens at the Clark, Red Hills, and Northwest study sites from 2013-2015. Models tested include single variable NDVI-based phenology metrics, single variable NDVI-based phenology metrics at multiple scales, multi-variable NDVI-based phenology metrics, additive and interactive site and year models, and a null model.

Model	K[a]	ΔAICc[b]	AICc[c]	w_i[d]	Deviance[e]
AMPscale1*Year	6	0.00	1523.48	0.74	-755.70
AMPscale1 + Year	4	2.80	1526.27	0.18	-759.12
AMPscale1	2	6.53	1530.01	0.03	-763.00
AMPscale1*EOSTscale3*TINscale3	8	7.39	1530.86	0.02	-757.37
Quadratic AMPscale1	3	8.51	1531.99	0.01	-762.98
AMPscale1 + EOSTscale3	3	8.52	1532.00	0.01	-762.99
AMPscale1+EOSTscale3+TINscale3	4	10.28	1533.76	0.00	-762.86
AMPscale1*EOSTscale3	4	10.51	1533.99	0.00	-762.98
AMP	2	11.60	1535.07	0.00	-765.53
Quadratic AMP	3	12.56	1536.04	0.00	-765.01
AMPscale2	2	12.98	1536.46	0.00	-766.22
MAXN + Site	4	12.99	1536.47	0.00	-764.22
MAXN*Site	6	15.18	1538.66	0.00	-763.29
MAXNscale1	2	15.52	1538.99	0.00	-767.49
TINscale1	2	16.92	1540.39	0.00	-768.19
MAXN+MAXT	3	17.84	1541.32	0.00	-767.65
DUR + MAXN	3	18.32	1541.80	0.00	-767.89
MAXN*MAXT	4	18.40	1541.87	0.00	-766.92
MAXN	2	19.96	1543.43	0.00	-769.71
Quadratic MAXN	3	20.47	1543.95	0.00	-768.96
Null	1	36.71	1560.19	0.00	-779.09

[a] Number of parameters
[b] The difference in Akaike's Information Criterion adjusted for small samples size
[c] Akaike's Information Criterion adjusted for small sample size
[d] Akaike weights
[e] Deviance (-2*loglikelihood)

Chapter 2 - MODIS-based Vegetation Phenology Metrics Predict Lesser Prairie-Chicken Habitat Use, Quality, and Reproduction Relative to Patterns of Greenness

Introduction

The dramatic and continuous loss of biodiversity around the world affects nearly every taxa and biome (Wilson 1989, Western 1992, Dirzo et al. 2014, Pimm et al. 2014). Recent attention has been brought to declines in the avian guild, with particular emphasis on grassland species. Unfortunately, over 700 million grassland birds have been lost since the 1970s with 74% of grassland species declining (Rosenberg et al. 2019). Declines in grassland birds have been attributed to habitat loss, habitat degradation, and climate change (Peterjohn and Sauer 1999, Crick 2004, Szabo et al. 2012, Loss et al. 2015, Stanton et al. 2018, Northrup et al. 2019). Substantial habitat loss puts added pressure on the configuration and abundance of high-quality habitat to foster survival and persistence (Andren 1994). Importantly, evaluating true habitat quality requires estimation of both habitat use and resulting demographic performance (e.g., vital rates) in an area (Van Horne et al. 1983). This may be especially true for the grassland obligate lesser prairie-chicken, which has experienced an estimated loss of 85% of its occupied range over the last 150 years (Van Pelt et al. 2013, USFWS 2014). While habitat selection and vital rates of lesser prairie-chickens have been well-documented using field-based measurements, efforts to predict habitat quality at relevant broad spatial scales have been limited. Remotely sensed vegetation phenology metrics may be useful in predicting quality of reproductive over broad spatial scales. Additionally, given the importance of the reproduction in the persistence of lesser prairie-chicken populations (Hagen et al. 2009), use of remotely sensed vegetation phenology products may elucidate the importance of the timing of nest initiation and hatch relative to patterns of vegetation growth.

The lesser prairie-chicken has suffered population declines since the 1980s (Hagen and Elmore 2016, Hagen et al. 2017, Garton et al. 2016). Population declines are primarily due to historic and ongoing conversion of native grasslands to cropland (Taylor and Guthery 1980, Askins et al. 2007, Rodgers 2016, Dahlgren et al. 2016), anthropogenic development (Hagen et al. 2004, Haukos and Zavaleta 2016, Van Pelt 2016, Plumb et al. 2018), and a loss of habitat quality (Haukos and Zavaleta 2016). Nest survival, brood survival, and juvenile recruitment can greatly influence lesser prairie-chicken population growth rates relative to adult survival, underscoring the importance of identifying quality reproductive habitat (Hagen et al. 2009, Sullins 2017, Ross et al. 2018). Linking these critical reproductive parameters (e.g., nest survival and brood survival) to habitat characteristics have been limited to date and hamper any ability to model habitat quality. Research, thus far, has provided extensive knowledge on reproductive habitat selection for the lesser prairie-chicken, but limited information on nest survival relative to vegetation characteristics (Hagen et al. 2009, Lautenbach et al. 2019). Given that the identification of quality reproductive habitat can be considered a hierarchical process, in that nests must survive before broods and juveniles are successful, it is important to determine whether spatial data can predict quality nesting habitat.

Nest-site selection is primarily linked to less bare ground, increased visual obstruction (typically between 2.0 and 3.5 dm at 75% visual obstruction), and greater percentage of litter compared to what is available at random sites (Giesen 1994, Pitman et al. 2005a, Patten and Kelly 2010, Lyons et al. 2011, Hagen et al. 2013, Fritts et al. 2016, Grisham et al. 2016, Lautenbach et al. 2019). Most research into nest survival indicates temperature, nest age, timing of nest initiation, and, to an extent, distance from anthropogenic features can impact nest survival, not measures of vegetation (Fields et al. 2006, Pitman et al. 2006, Grisham et al. 2016, Lautenbach et al. 2019). In fact, one of the only established links between nest survival and vegetation is with measures of visual obstruction (VO). Recent work has demonstrated that nest survival is optimized when 75% VO is between 2.0 dm and 4.0 dm (Lautenbach et al. 2019), which is supported by similar results from other research findings (Davis 2009, Grisham et al. 2014, Parker et al. 2022). However, it is important to note that the selection and survival studies discussed above are typically based on measurements of vegetation in potential "microhabitats" (e.g. 50 m^2) that are randomly or systematically placed throughout a study area. Despite the utility of vegetation data at several locations, it is thought that habitat quality for lesser prairie-chickens manifests at a broader scale, not necessarily at point locations (Haukos and Zavaleta 2016, Gehrt et al. 2020). Therefore, measuring selection and evaluating survival at additional scales associated with used and available locations may yield additional insights into habitat selection (Chapter 1) and quality. Additionally, evaluating differences between successful and unsuccessful reproductive sites may also yield insight into habitat use at relevant broad spatial scales. To do this, one promising method is through the use of remotely sensed vegetation indices.

The Normalized Difference Vegetation Index (NDVI) is a remotely sensed index that measures the difference between the amount of red light and infrared light being reflected off living vegetation and is calculated from satellite or aerial imagery (Rouse et al. 1974). The difference in reflectance describes the greenness and density of vegetation, making NDVI a proxy for aboveground biomass and productivity (Rouse et al. 1974, Tucker 1979). Importantly, we can derive additional measures from NDVI, such as vegetation phenology metrics that describe the growing season phenology of vegetation (Table 2.1). Depending on the imagery used, phenology metrics can be calculated at extremely large spatial extents, making them useful in broad-scale monitoring of species reliant on variable vegetation characteristics across all life stages, such as the lesser prairie-chicken.

Vegetation indices, including NDVI, have been used in ecological research for decades, and have been successfully linked to survival for a number of species. For example, annual survival of the migratory white stork (*Ciconia ciconia*) increases when primary productivity, as measured by NDVI, is high in winter stopover areas, and lower when primary productivity is low (Schaub et al. 2005). Here, NDVI was used as a proxy for primary productivity and, by extension, food availability. It is believed that low values of NDVI reflect lower food availability, which negatively affected survival of white stork (Schaub et al. 2005). Barn swallow (*Hirundo rustica*) survival in Europe is also positively related to NDVI, which allowed for the prediction of wintering and migration areas in South Africa (Szép et al. 2006). Other species for which survival has been linked to NDVI include Egyptian vultures (*Neophron percnopterus*; Grande et al. 2009), mule deer (*Odocoileus hemionus*; Hurley et al. 2014), big horn sheep (*Ovis canadensis*), Alpine ibex kids (*Capra ibex*; Pettorelli et al. 2007), and, although weakly predictive, greater sage-grouse chicks (*Centrocercus urophasianus*; Guttery et al. 2013). Given the apparent utility of linking NDVI-based phenology metrics to measures of survival for multiple species combined with the reliance of lesser prairie-chickens on varying vegetation composition and structure across life stages, I expect that NDVI-based phenology metrics may be successful in measuring habitat quality at relevant broad spatial scales.

Lastly, aside from its potential utility in measuring habitat quality, NDVI-based phenology metrics may also elucidate the importance of the timing of nest initiation and hatch relative to patterns of vegetation growth. Studies show that nests initiated earlier in the reproductive season experience greater success compared to nests initiated later in the reproductive season (Fields et al. 2006, Pitman et al. 2006, Lautenbach et al. 2019). Reasons for this pattern are unclear, but may have something to do with resource availability as represented by increases in vegetation productivity. Many avian species time reproductive events to peak resource abundance but are now experiencing phenological mismatches due to climate change, which can have negative fitness consequences (Walther et al. 2002, Visser and Both 2005). Whether the lesser prairie-chicken times reproductive events to peak food availability is unknown. Evaluating timing of hatch relative to specific phenology metrics (the start of the growing season and the peak of the growing season) may reveal patterns heretofore uninvestigated and consequently reveal new information about the reproductive ecology of this iconic Great Plains species.

Ultimately, there is still more to learn regarding the reproductive ecology of lesser prairie-chickens. Because management recommendations typically point to improved habitat quality as a primary conservation goal for lesser prairie-chickens, innovative methods using remote sensing to predict high priority reproductive habitat and monitor vegetation response to management strategies within Kansas are needed (Chapter 1). I hypothesized that nest initiation and hatch are timed to the period between the start of the growing season and the peak of the growing season, allowing females with broods to access resources as they develop. Specifically, I predicted that nests would be initiated close to the start of the growing season (SOST; Table 2.1) and hatch would occur prior to the peak of the growing season (MAXT). I also hypothesized that phenology metrics would be indicative of underlying vegetation structure and composition (e.g., warm season vs. cool season grasses) that would vary among successful and unsuccessful nests. Specifically, I predicted that successful nest sites would have earlier SOST values compared to unsuccessful nests, and values of maximum NDVI (MAXN) would be greater at successful nest sites.

Peak primary productivity is a direct proxy of MAXN, which I expect to be important at successful brood sites due to relationships with increased arthropod food abundance (Sweet et al. 2015, Fernández-Tizón et al. 2020, Traba et al. 2022). Lastly, I hypothesized that phenology metrics at broad spatial scales would predict nest survival for the lesser prairie-chicken. I predicted that MAXN or time integrated NDVI (TIN) would best predict nest survival. Peak resource abundance, as represented by MAXN, is important for nesting females as well as brood-rearing females due to the high energetic requirements associated with nesting (Martin 1987). Similarly, TIN is a direct proxy for the density of vegetation across the growing season. Percent cover of grasses and, to a lesser extent, forbs, are important for nesting females (Hagen et al. 2013, Grisham et al. 2014, Lautenbach et al. 2019), which I expected to be reflected in TIN.

Methods

Study area

My study area occured within 2 of the 4 ecoregions occupied by lesser prairie-chickens: the Short-grass Prairie/CRP Mosaic and Mixed-grass Prairie. The study sites were Clark, Northwest, and Red Hills, all located in western Kansas (Figure 2.1). Data from these study sites were pooled from previous research during 2013, 2014, and 2015. One notable quality of the lesser prairie-chicken range is the pronounced precipitation gradient, where the amount of precipitation increases from west to east. Because of this, there is annual variability in the amount of precipitation received at each study site. In the westernmost portion of the lesser prairie-chicken range, average annual precipitation ranges from 27.8 to 40.5 cm (Grisham et al. 2016). In the easternmost portion of the lesser prairie-chicken range, average annual precipitation is larger and ranges from 63.9 and 76.3 cm (Grisham et al. 2016).

The Northwest study site was located in northwestern Kansas in the Short-grass Prairie/CRP Mosaic Ecoregion and encompassed Logan and Gove counties. Research was primarily conducted on private lands, as well as on Smoky Valley Ranch owned by The Nature Conservancy. Dominant land uses across the Northwest study site included grazing, CRP grasslands, and row-crop agriculture. Soil type was primarily silt loam. Dominant grasses differed between the short-grass working grasslands and planted CRP grasslands. In the CRP grasslands of this ecoregion, dominant grasses include sideoats grama (*Bouteloua curtipendula*), little bluestem (*Schizachyrium scoparium*), big bluestem (*Andropogon gerardii*), switchgrass (*Panicum virgatum*), and Indiangrass (*Sorghastrum nutans*). Dominant forbs in the CRP grasslands include yellow sweet clover (*Melilotus officinalis*), white sweet clover (*Melilotus alba*), prairie coneflower (*Ratibida columnifera*), purple prairie clover (*Dalea purpurea*), and Illinois bundleflower (*Desmanthus illinoensis*; Lautenbach et al. 2019). In the short-grass prairie working lands, dominant grasses included blue grama (*Bouteloua gracilis*), buffalograss (*Bouteloua dactyloides*), hairy grama (*Bouteloua hirsuta*), little bluestem, big bluestem, western wheatgrass (*Pascopyrum smithii*), and sideoats grama. Dominant forbs in the short-grass prairie working lands included western ragweed (*Ambrosia psilostachya*), Russian thistle (*Salsola* sp.), Illinois bundleflower, annual buckwheat (*Eriogonum annum*), prairie sunflower (*Helianthus petiolaris*), sand milkweed (*Asclepias arenaria*), nine-anther dalea (*Dalea enneandra*), and broom snakeweed (*Gutierrezia sarothrae*). Lastly, dominant shrubs across the Northwest study site include yucca (*Yucca glauca*) and sand sagebrush (*Artemisia filifolia*; Sullins et al. 2018, Lautenbach et al. 2019).

The Clark and Red Hills study sites were both located on private lands in the Mixed-grass Prairie, with the Clark study site bordering the sand sagebrush prairie. Soil composition at the Clark study site was primarily fine sandy loams, loamy fine sands, and fine sands (Sullins et al. 2018). At the Red Hills study site, soil composition was primarily clay, clay loam, and sandy loam (Sullins et al. 2018). Dominant land uses at these study sites were cattle grazing and row-crop agriculture. At both study sites, dominant grasses included little bluestem, big bluestem, blue grama, hairy grama, sand dropseed (*Sporobolus cryptandrus*), alkali sacaton (*Sporobolus airoides*), switchgrass, sideoats grama, and buffalograss. Dominant forbs at both study sites included western ragweed, kochia (*Kochia scoparium*), Russian thistle, Louisiana sagewort (*Artemisia ludiviciana*), annual sunflower (*Helianthus annuus*), broomweed (*Amphiachyris dracunculoides*), and broom snakeweed. The most abundant shrubs included sand sagebrush, eastern red cedar (*Juniperus virginiana*), sand plum (*Prunus angustifolia*), and fragrant sumac (*Rhus aromatia*; Sullins et al. 2018, Lautenbach et al. 2019).

Capture and monitoring:

From mid-March through mid-May of 2013, 2014, and 2015, I captured lesser prairie-chickens at 3 study sites in western Kansas using drop nets and walk-in funnel traps (Haukos et al. 1990, Silvy et al. 1990). Captured females were marked with either a 22-g solar powered GPS satellite transmitter (PTT-100, Microwave Telemetry, Inc., Columbia, MD) or a 15-g very-high-frequency (VHF) transmitter. For GPS-marked females, locations were recorded every 2 hours between 0500-2300. For VHF-marked females, birds were tracked manually and locations were triangulated 3-4 times per week.

I monitored and evaluated spatial patterns of GPS- and VHF-marked females during the nesting season to determine when a nest was initiated following Lautenbach et al (2019). Nesting behavior of a GPS-marked hen was indicated by multiple transmitted locations at the same point and minimal movement around that point. For VHF-marked hens, a nest was deemed initiated if the female was located in the same spot >3 times in a row. Following confirmation of initiation, I searched for and flushed females from the nest to count, weigh, measure, and float eggs to ascertain an estimated hatch date. I recorded the Universal Transverse Mercator coordinate system locations of nests using the WGS 1984 Zone 14N datum and vacated the nest site as quickly as possible. As the nesting season progressed, I visited nests a second time once the female left the area to determine the outcome of the nest (successful or failed).

Remotely sensed data collection:

To evaluate the influence of vegetation phenology metrics on demography and successful versus unsuccessful reproductive sites, I downloaded freely available phenology imagery from the Aqua Moderate Resolution Imaging Spectroradiometer (hereafter MODIS) satellite. More specifically, I used the C6 Aqua Western 250 m eMODIS RSP (remote sensing phenology) data, downloaded from the USGS Phenology Viewer (Jenkerson et al. 2010, Brown et al. 2015; Table 2.1; https://doi.org//10.5066/F7PC30G1). Images from this collection are delivered at a 250-m pixel resolution, and are maintained and processed by the USGS Earth Resources Observation and Science Center (EROS). The eMODIS images are based on weekly composites of eMODIS NDVI data (USGS 2021) and are temporally smoothed to eliminate irregular spikes of NDVI estimates that are considered spurious. From the weekly NDVI composites and subsequent year long time series, 9 vegetation phenology metrics are calculated (Table 2.1).

One notable quality about the eMODIS imagery is that there are pixels within which phenology metrics were unable to be calculated. The value assigned to no data cells was either 0 or -1000. Similarly, cells identified as water were also given specific values, either 255 or 1000. If values of -1000, 255, or 1000 were included in my analyses, results could have been negatively impacted. To address this, I converted any cell containing 0, 1000, -1000, or 255 to be "No Data" using the "Set Null" function in ArcGIS 10.8. All locations with "No Data" were excluded from analyses.

Nest survival:

I organized nest data into a CSV file containing first found, last present, last checked, and outcome of all nests. To evaluate relationships between vegetation phenology metrics and daily nest survival, I constructed a candidate model set with 46 *a priori models* using package "RMark" in program R (Laake 2013, R Core Development Team 2022). I used a 38-day exposure period to estimate survival across the nesting season and used the delta method assuming independence to estimate error around the estimate (Powell 2007). Variables in the a priori model set were single variable vegetation phenology metrics at multiple scales around nest sites (250-m pixel scale, 370 m, 500 m, 1 km, and 3 km; Table 2.2). I ranked models using Akaike's Information Criterion adjusted for small sample size (AICc; Burnham and Anderson 2002). Models within 2 ΔAICc from the top ranked model were considered competitive. I evaluated beta coefficients of all top-ranked models. Beta coefficients with overlapping 95% confidence intervals were considered uninformative.

Comparison of phenology at successful versus unsuccessful nest and brood sites:

Using the “Extract Multi Values to Point” tool in ArcGIS 10.8, I extracted values of 9 phenology metrics at nest and brood sites from 2013, 2014, and 2015. In the CSV file that I used to organize data, I included a column that stated whether the nest was successful and whether the brood site was the location of a successful or unsuccessful brood. I was interested in whether there were differences in the means of phenology metrics at successful versus unsuccessful reproductive sites. First, I used a Hotelling’s T^2 test to determine whether there was a multivariate difference of phenology at successful and unsuccessful nest and brood sites. Once a multivariate difference was confirmed ($P < 0.05$), I implemented a Welch’s two-sample t-test assuming unequal variances to compare 9 phenology metrics (Table 2.4) at successful and unsuccessful reproductive sites.

Timing of nest initiation and hatch relative to patterns of greenness:

I exclusively used first nest attempts to elucidate the importance of the timing of nest initiation and hatch relative to patterns of vegetation growth. I compiled a list of first nests from 2013, 2014, and 2015 at the Clark, Red Hills, and Northwest study sites. I extracted SOST and MAXT values at each nest. To determine the difference between nest initiation dates and SOST, I subtracted SOST values from Day of Year (DOY) laying values. Similarly, to determine how many days nests hatched prior to MAXT, I subtracted DOY hatch dates from MAXT.

Results

Nest survival:

The single variable Time of Maximum NDVI (MAXT) at the 500-m scale ($\beta = -0.009$, SE = 0.004) best predicted lesser prairie-chicken nest survival across study sites and years and carried 18% of model weight (Table 2.2). Nest survival was maximized when MAXT was 160, which corresponds to locations having peak greenness values on June 9th and decreased linearly as MAXT increased (Figure 2.2). There were 3 additional models that fell within 2 ΔAICc of the top ranked model including TIN at the 3-km scale ($\beta = 3.15$, SE = 1.34), MAXT at the 250-m scale ($\beta = -0.006$, SE = 0.003), and MAXT at the 370-m scale ($\beta = -0.007$, SE = 0.003), all of which outranked the null model (Table 2.2). The beta coefficients of each single variable competitive model did not overlap zero at the 95% confidence interval and were therefore significant.

Comparison of phenology at successful versus unsuccessful nest and brood sites:

Among years, I compared phenology metrics at a total of 224 nest sites. Of the 224 nests, 150 nests were unsuccessful and 74 were successful. Of the 9-phenology metric means that were compared, 2 were significantly different between successful and unsuccessful nests: TIN and MAXT. At successful nests, TIN was greater by 0.02 ($P = 0.05$) and MAXT was earlier by 8 days ($P = 0.04$). Means of the remaining 7 phenology metrics (AMP, DUR, SOST, SOSN, MAXN, EOST, and EOSN) did not differ among successful and unsuccessful nests (Table 2.3).

At 266 sites of successful brood-rearing females and 55 sites of failed broods, MAXT and EOSN differed between successful and unsuccessful brood sites. MAXT was 12 days later at successful brood sites ($P = 0.003$) and EOSN was greater by 0.01 ($P = 0.01$). The remaining 7 phenology metrics did not significantly differ between successful and unsuccessful brood sites (Table 2.4).

Timing of nest initiation and hatch relative to patterns of greenness:

I monitored 43 nests in 2013 (39 first nest attempts), 115 in 2014 (80 first nest attempts), and 66 nests in 2015 (57 first nest attempts). Site-specific means of laying dates and hatch dates from 2013-2015 are found in Table 2.5. In general, first nests were initiated ~within 20 days of SOST (Figure 2.3). In 2013, the mean laying date of nests across study sites was 125 ± 10 (May 5th). The mean SOST at nest sites among study sites was 121 ± 25 (May 1st). Thus, first nests were, on average, initiated 4 days after SOST. In 2014, the mean laying date of nests across study sites was 118 ± 14 (April 28th), and mean SOST at nests across study sites averaged 20 days later (138 ± 16; May 18th). Lastly, in 2015 the mean laying date of nests across study sites was 115 ± 9 (April 25th); the mean SOST at nests across study sites was one day earlier (114 ± 6). Overall, nest initiation occurs within a window close to the start of the growing season.

When hatch dates were evaluated in relation to the date of maximum greenness (MAXT), it was clear that hatch of all first nest attempts occurred prior to the peak of the growing season (MAXT; Figure 2.3). In 2013, the mean hatch date across study sites was 160 ± 12 (June 9th), with the mean MAXT at nest sites a mean of 62 days later (222 ± 40; August 10th). In 2014, the mean hatch date across study sites was DOY 165 ± 17 (June 14th), with the mean MAXT at nest sites 60 days later (205 ± 16; July 25th). Last, in 2015 the average hatch date across study sites was DOY 157 ± 12 (June 6th) with MAXT following 30 days later (187 ± 33; July 6th). Site-specific means of SOST and MAXT at nest sites from 2013-2015 are in Table 2.6.

Discussion

Use of NDVI and NDVI-based phenology metrics in the evaluation of habitat quality for lesser prairie-chickens in the short- and mixed-grass prairies has not been reported, though attempts to link remotely sensed vegetation phenology to nest site-selection, nest survival, and home range sizes were attempted in the sand shinnery oak prairie, albeit largely unsuccessfully (de la Piedra 2017). Therefore, I provide some of the first evidence successfully linking habitat quality to broad-scale remotely sensed vegetation phenology metrics. Specifically, I found that lesser prairie-chicken nest survival was informed by MAXT at the 500-m spatial scale. Additionally, I also used phenology metrics to elucidate the timing of critical reproductive events (i.e., laying date and hatch date) relative to patterns of greenness and documented that lesser prairie-chickens time laying and hatch between the start of the growing season and the peak of the growing season.

Nest Survival:

Historically, it has been difficult to link nest survival to vegetation characteristics, despite the wealth of informative vegetation-based predictors for nest site-selection. It appears that eMODIS 250-m remote sensing phenology images can predict nest survival and may be essential to advancing our ability to predict nest survival in grasslands. Specifically, I was able to link 500-m resolution spatial data to nest survival, with MAXT informing nest survival. Nest survival was greatest at earlier dates of MAXT with peak survival occurring at DOY 160 and decreasing as MAXT progressed. Interestingly, nest survival was greatest at DOY 160, but the mean MAXT at nest sites was 38 days later, on DOY 198.

There may be several reasons for the observed differences between MAXT optimized for modeled nest survival and MAXT at successful nests are different. First, it is possible that differences in grass and forb composition around nest sites are reflected in the results. For example, research has shown that warm-season grasses and cool-season grasses exhibit distinct NDVI curves, with cool-season grasses reaching peak NDVI earlier than warm-season grasses (Wang et al. 2010). Although residual warm-season grasses are predominantly used by lesser prairie-chickens for nesting, there may be better cover or greater resources in areas with some cool-season grasses and forbs earlier in the nesting season. Additionally, the differences between values of MAXT in nest survival and at successful versus unsuccessful nests may also indicate that heterogeneity of vegetation remains important from not only a structural perspective, but also from a phenological perspective. Ultimately, and most importantly, the overarching pattern associated with nest survival and means at successful nest sites is that MAXT occurs earlier in the growing season.

Although eMODIS RSP phenology metrics are useful from a broad-scale monitoring perspective, with the use of my methodologies as a stepping stone into additional remotely sensed monitoring efforts of lesser prairie-chicken habitat, it may be beneficial to use finer resolution imagery such as Landsat (30-m resolution) or Sentinel 2 (10-m resolution) in similar analyses, which would require time-series analyses to produce phenology estimates because vegetation phenology metrics are generated based on repeated measures of NDVI (see one of the first reported methods of time-series by Holben 1986 and a review of time-series methodologies in Li et al. 2021). There are many uses for broad-scale results such as mine, but instances in which finer scale imagery may be useful include monitoring areas with the highest densities of lesser prairie-chickens or within areas of identified priority grasslands. Monitoring phenology at finer resolutions within priority and high priority grasslands may give wildlife managers better insights of vegetation structure, composition, heterogeneity, and phenology as well as any changes related to habitat area and habitat quality that may occur within priority and high priority areas.

Comparison of phenology at successful versus unsuccessful nest and brood sites:

Relatedly, there were significant phenological differences at successful and unsuccessful nest and brood sites. In my study, MAXT occurred earlier at successful nests(DOY 198) compared to 8 days later at unsuccessful nests (DOY 206). Although this relationship was statistically significant, the 8-day difference may be minimal. Regardless, while the 8-day difference appears short, it may be just enough time to affect resources, such as arthropod growth (Juliano 1986) and plant growth (Risser and Johnson 1973) around the nest site. Differences in MAXT at successful and unsuccessful brood sites, however, may tell a different story.

At successful brood sites, MAXT occurred on DOY 200, which is within 2 days of MAXT for successful nest sites. Each of these dates would provide broods access to increases in resource availability for approximately 45 days following mean hatch date, which, on average among years, occurs on DOY 155 (June 4th). The fact that MAXT at successful nest and brood sites are similar may indicate that locations with primary productivity increasing to mid-July may provide optimal conditions and resource availability for broods and brood-rearing females. Additionally, this 45-day window may have other implications. For example, it has been reported that chicks reach asymptotic body mass around day 50 and juveniles with greater body mass 50-60 days post-hatch experienced greater survival (Pitman et al. 2005b, 2006). Thus, it stands to reason that areas with resources increasing over a longer time period would be more beneficial for chicks and females.

At unsuccessful brood sites, MAXT occurred on DOY 188 (July 7th), which is 12 days prior to successful brood locations. Considering that the mean hatch date across years is DOY 155 (June 4th), this would only provide a 33-day window of increasing resource availability. Although I did not investigate this, it is possible that this shorter window is a barrier to resource acquisition and, ultimately, survival.

Aside from MAXT, which differed between successful and unsuccessful nest and brood sites, there were other significant differences in phenology as well. At successful nest sites, TIN was greater than at unsuccessful nest sites. The TIN metric directly translates to greater density of vegetation, and by extension, the amount of vegetative cover. The importance of cover at lesser prairie-chicken nest sites is well established in the literature, as nest sites are typically comprised of greater percentages of forb and grass cover compared to what is available at random sites (Hagen et al. 2013, Grisham et al. 2014, Lautenbach et al. 2019). That TIN is significantly greater at the 250-m scale indicates that the density of vegetation 250 m surrounding successful nest sites is greater than at unsuccessful nests, which likely also benefits nesting females when they make movements outside of the nest.

Lastly, EOSN is greater by 0.01 at successful brood sites than unsuccessful brood sites. Brood-rearing females have been observed to move older broods into more productive wet areas where resources may remain later into the growing season (D. S. Sullins and D. A. Haukos, Kansas State University, personal communication). It is possible that movements into wetter areas are being reflected here, though the small difference between EOSN at successful versus unsuccessful brood sites makes this equally unlikely, as this difference is fairly negligible despite its statistical significance. Brood movements into wetter areas is an area of lesser prairie-chicken research that is lacking, though these types of movements and space use have been documented in brood-rearing greater sage-grouse (Danvir 2002, Crawford et al. 2004, Dzialak et al. 2011, Dinkins et al. 2014). A better understanding of the role that EOSN plays in lesser prairie-chicken space use would be useful given the lack of literature to support this finding. A promising start may lie within evaluating the role of areas more likely to hold soil moisture (e.g., Compound Topographic Index; Gessler et al. 1995) in brood use and any associated phenological patterns.

Timing of nest initiation and hatch:

Annual life stages (such as reproduction) and movement of wildlife are often timed to match pulses in vegetation growth associated with periods of abundant palatable food and cover (Drent et al. 1978, Martin 1987, van der Graff et al. 2006, Si et al. 2015, Duursma et al. 2019, Stoner et al. 2020). This phenomenon is most often observed in migratory species, allowing individuals to temporally elongate benefits from peak vegetative growth (greenness) spread over altitudinal and latitudinal gradients (Bischof et al. 2012, Fryxell and Avgar 2012, Blake et al. 2013, Shariatinajafabadi et al. 2014, Aikens et al. 2017), but is studied in resident species across other taxa as well (Middleton et al. 2018). The idea of species following this “green wave” was first hypothesized by Drent et al. (1978) to describe the migration patterns of brent geese (*Branta bernicla*) and barnacle geese (*Branta leucopsis*) as a function of food availability. Both species moved northward with the progression of vegetation green up, which provided them with more palatable food and a better energy balance in time for the breeding season. A similar hypothesis referred to as the “forage maturation hypothesis”, which states that forage rate is optimized at intermediate biomass (i.e. before senescence) and is thought to explain patterns of ungulate migration (Fryxell 1991, Hebblewhite et al. 2008). Regardless of the hypothesis, by tracking changes in vegetation phenology, individuals, herds, and flocks are able to take advantage of resources as they first develop when they are high in nutrient content and most palatable. Although an abundance of research focuses on vegetation green up relative to migratory species, non-migratory species can also maximize the benefits of peak growing season by timing critical life stages to match periods of abundant resources (Bischof et al. 2012, Middleton et al. 2018, Wann et al. 2019, Stoner et al. 2020). A number of avian species are hypothesized to time hatch to periods of greater food availability for chicks, given the high caloric needs and protein demands of both broods and brood-rearing females (Perrins 1970, Van Noordwijk et al. 1995. Dunn 2004, Wann et al. 2019, Stoner et al. 2020). Mismatches of the synchrony between reproductive events and food availability can have negative fitness consequences on both adults and chicks (Thomas et al. 2001, te Marvelde et al. 2011, McKinnon et al. 2012, Wann et al. 2019, Simmonds et al. 2020). My research indicates that non-migratory lesser prairie-chickens time reproductive events (nesting and hatch) to the period between the start of the growing season and peak of the growing season (Figure 2.3), which I hypothesize may be to optimize food availability and abundance for chicks.

The date of the start of the growing season (SOST) simply refers to the period of time at which there is a measurable increase of NDVI above a baseline. As the growing season progresses, NDVI inevitably reaches a peak (MAXT and MAXN) where greenness and canopy density are at maximum levels, and various resources are increasing daily. Interestingly, measures of NDVI have been correlated with a number of resources including arthropods (Sweet et al. 2015, Fernández-Tizón et al. 2020), which are an important food source for many avian species, including the lesser prairie-chicken (Savory 1989, Sullins et al. 2018). For example, in European shrublands and mixed-grass shrublands, arthropod biomass was positively associated with numerous vegetation indices (enhanced NDVI, green NDVI, green soil adjusted vegetation index, among others) calculated at 4-cm and 10-m spatial resolutions (Traba et al. 2022). In temperate European grasslands, spring arthropod biomass increased with increasing NDVI, which researchers suggest is an effective proxy for spring food availability (Fernández-Tizón et al. 2020). Whether or not these relationships occur in the semi-arid Great Plains remains untested, but the importance of arthropod availability in lesser prairie-chicken brood diets is inarguable and may be related to measures of NDVI (Sullins et al. 2018).

After hatching, lesser prairie-chicken chicks grow rapidly and have high caloric demands (Sullins et al. 2018). Ideally, critical resources should be available within a relatively small area given the limited mobility of chicks (Van Pelt et al. 2013, Sullins et al. 2018, Verheijen et al. 2020). If the hatch date of lesser prairie-chicken nests occur before the peak of the growing season, chicks and brood-rearing females will presumably have maximum access to arthropods (and forbs, another important food source) as they emerge and increase in abundance. Additionally, hatching prior to MAXT would likely provide chicks with arthropods that are smaller, which would be easier for a small chick to consume. If arthropod biomass increases with increasing NDVI in the semi-arid grasslands of western Kansas, it is likely that arthropods are reaching peak biomass at a similar time to when MAXT is occurring.

In 2013, 2014, and 2015, nests were laid 4 days after SOST, 20 days before SOST, and 1 day after SOST, respectively. Patterns of nest initiation occurring near the start of the growing season and hatching prior to the peak of the growing season has been observed in greater sage-grouse (*Centrocercus urophasianus*) in Utah where sage-grouse initiated nests 22 days after the start of the growing season and hatch occurred 2-3 weeks prior to the peak of the growing season (Stoner et al. 2020). This is thought to provide greater sage-grouse chicks with food for a longer period of time. Consequences of hatching later in relation to food availability can be seen in greater snow goose (*Chen caerulescens atlantica*) goslings. Goslings that hatched later had access to fewer nutrient rich foods compared to those that hatched earlier, indicating that hatching earlier than peak food availability may be more beneficial to chicks than hatching at or following the peak of food availability (Lepage et al. 1998). Similarly, sites of unsuccessful lesser prairie-chicken broods reached MAXT later than sites of successful broods.

Understanding potential relationships between the timing of reproductive events and phenological dates is particularly important in the context of climate change. Species that have evolved to match critical life stages to patterns of vegetation phenology have been, or are predicted to be, negatively affected by climate change (Visser et al. 2004, 2006, 2021; Both et al. 2005, 2006; Post and Forchhammer 2007, Wann et al. 2019). As climate change has progressed over the last few decades, multiple avian species have experienced phenological mismatches across numerous climate zones, with mismatches often most apparent in higher latitudes but observed nonetheless in mid-latitudes. Great tits (*Parus major*) have synchronized the food requirements of chicks with caterpillar abundance, which is reflected in the timing of nest initiation (Visser et al. 2006). Over time, temperatures have increased and as a result the time of peak food abundance has shifted to earlier dates, but the laying dates (and, by extension, hatch dates) of great tits have not shifted to match the altered timing of peak food availability. The phenological mismatch between peak food abundance chick hatch dates have resulted in fewer fledglings and lower mass of fledglings (Visser et al. 2006). Similarly, food abundance (arthropod and vegetation) for white-tailed ptarmigan chicks and brood-rearing females is best predicted by NDVI, and negative consequences occur due to seasonal mismatch. Seasonal mismatch was derived by calculating the area under the curve from a generalized additive model (GAM) that incorporated estimates of NDVI. High values of seasonal mismatch indicated that broods were being reared during a time that did not correspond to peak resource abundance. Survival is lower for chicks hatching at greater values of seasonal mismatch and younger chicks are more likely to be negatively affected by mismatches than older chicks (Wann et al. 2019).

Conclusions:

I have provided evidence that remotely sensed phenology data can be linked to nest survival at relevant spatial scales by using 250-m eMODIS phenology images, and timing of maximum NDVI is informative of nest survival. Additionally, I was able to link phenology metrics to brood survival by evaluating successful versus unsuccessful brood locations, though the sample was not large enough for substantial modeling efforts. Specifically, I have provided evidence that at the 250-m scale, successful and unsuccessful brood sites significantly differ from one another from a phenological perspective. Phenological differences were also observed at successful versus unsuccessful nest sites, the results of which further reinforced the importance of TIN, and therefore the density of vegetation, at nest sites. Phenological differences between successful and unsuccessful reproductive sites reinforces the idea that patterns of selection are evident at broader scales as well as the finer scales at which it is typically measured.

Last, with this research, I have also provided evidence that lesser prairie-chickens appear to time nest initiation and hatch to the period between the start of the growing season and the peak of the growing season. Though this has been documented in other grouse, it has not been formally evaluated for the lesser prairie-chicken. I expect that the timing of nest laying and hatch are related to peak food availability for chicks and brood-rearing females. However, whether food availability is a factor in reproductive timing will need additional investigation, ideally by incorporating an arthropod study into this work. Additionally, given the effects that climate change has had and will continue to have across the Great Plains, it may be useful to determine whether phenological metrics have been altered over the decades as a result of climate change, and whether the laying and hatch dates of lesser prairie-chickens have changed in response to any potential phenological changes using long-term data sets.

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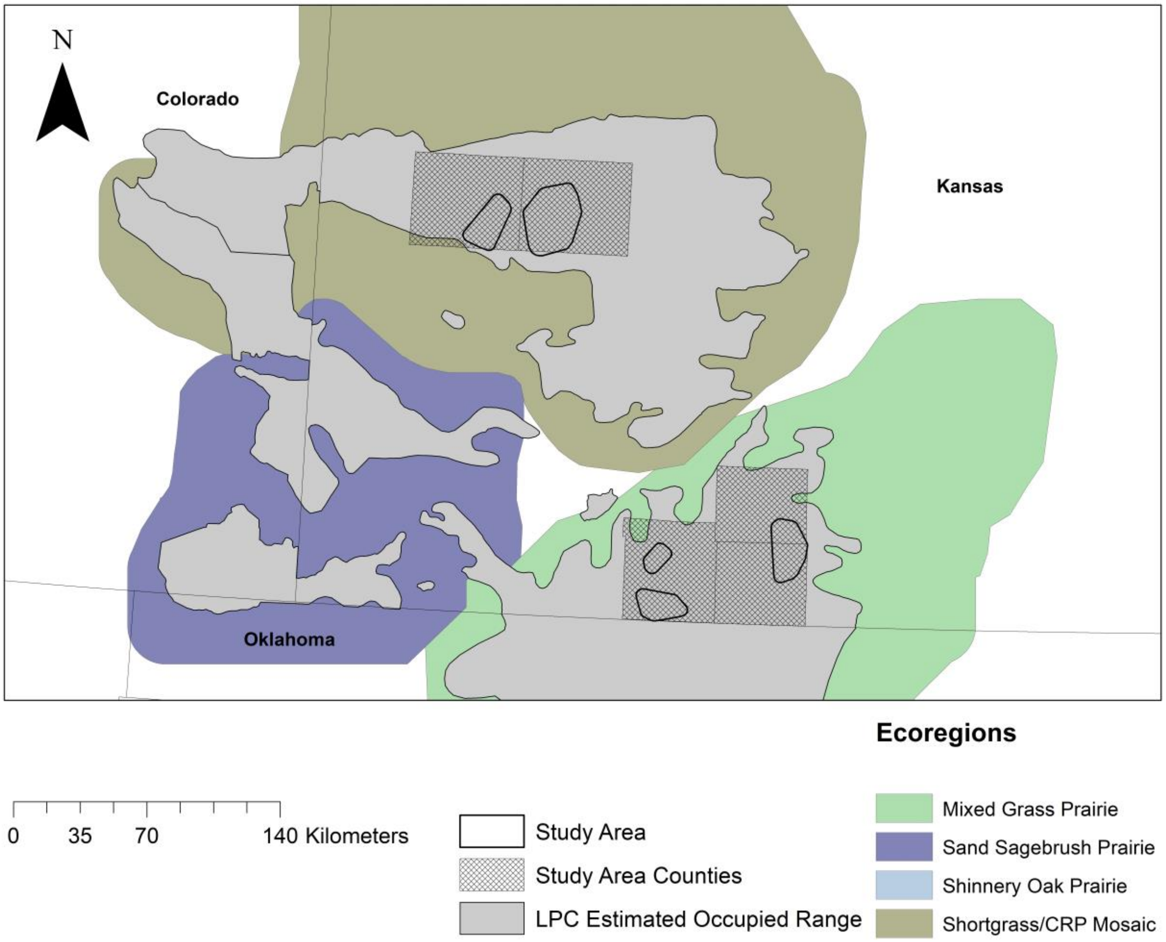

Figure 2.1. Map of the study area (Red Hills, Northwest, and Clark) covering Logan, Gove, Clark, Kiowa, and Comanche counties. Study areas are located within the Mixed-Grass and Short-Grass/Conservation Reserve Program (CRP) Mosaic of the lesser prairie-chicken range in western Kansas.

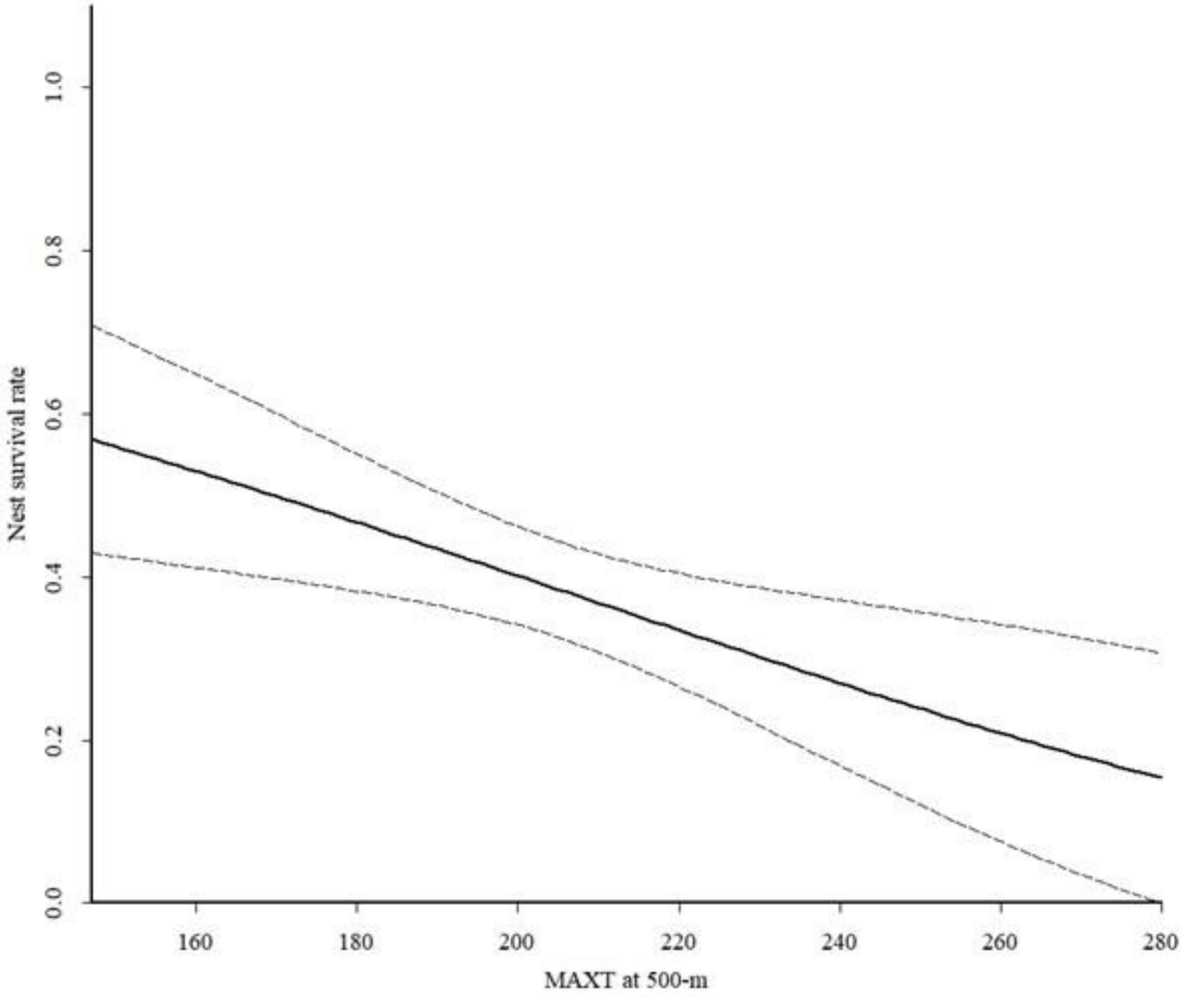

Figure 2.2. nest survival and 95% confidence intervals based on a 38-day exposure for lesser prairie-chickens at 3 study sites (Clark, Northwest, and Red Hills) as a function of Time of Maximum NDVI at the 500-m scale (MAXT).

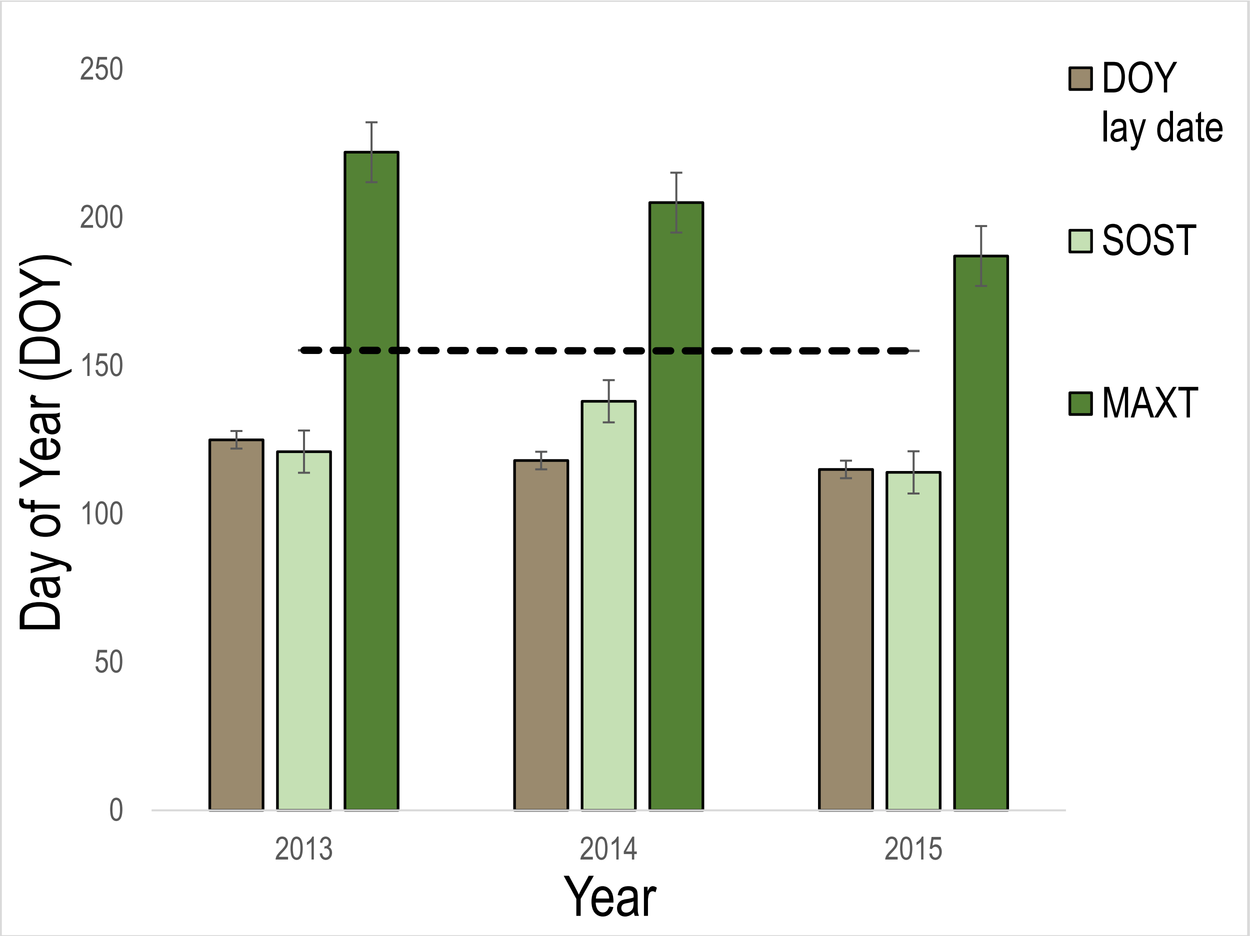

Figure 2.3. Mean DOY laying dates of first nest attempts are depicted in brown, the mean start of the growing season date (SOST) is depicted in light green, and the mean time of maximum NDVI is depicted in dark green. The error bars represent standard deviation among sites each year (2013, 2014, and 2015). The dashed line represents the mean DOY hatch date among years.

Table 2.1: The 9 NDVI-based vegetation phenology metrics used in my analyses and their descriptions. All metrics are calculated and maintained by the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center. Each phenology metrics is calculated from weekly NDVI composites over a one-year period. Data is freely available from the USGS Phenology Viewer (https://phenology.cr.usgs.gov/viewer/).

Phenology Parameters	Description
SOST → Start of the growing season, time	Day of year at which a measurable photosynthetic increase takes place after senescence.
SOSN → Start of the growing season, NDVI	NDVI value of the first measurable photosynthetic increase after senescence.
EOST → End of the growing season, time	Day of year at which there is a measurable decline in photosynthetic activity.
EOSN → End of the growing season, NDVI	NDVI value on the day that there is a measurable downward trend in photosynthesis.
MAXN → Maximum NDVI	Highest level of photosynthetic activity detected in the growing season.
MAXT → Maximum NDVI, time	Day of year associated with the MAXN.
AMP → Amplitude	Difference between the SOSN and MAXN values.
DUR → Duration	Length of the growing season (i.e. the difference between the SOST and EOST).
TIN → Time Integrated NDVI	Cumulative integrated photosynthetic activity across the growing season.

Table 2.2: 11 out of 46 *a priori* candidate models used to model nest survival for lesser prairie-chickens at the Clark, Red Hills, and Northwest study sites from 2013-2015. Models tested include single variable NDVI-based phenology metrics, single variable NDVI-based phenology metrics at multiple scales, multi-variable NDVI-based phenology metrics, additive and interactive site and year models, and a null model.

Model	K[a]	ΔAICc[b]	AICc[c]	w_i[d]	Deviance[e]
MAXTscale2	2	0.00	1408.18	0.18	1404.18
TINscale4	2	1.23	1409.41	0.10	1405.41
MAXT	2	1.71	1409.89	0.08	1405.89
MAXTscale1	2	1.95	1410.13	0.07	1406.13
TINscale3	2	2.45	1410.63	0.05	1406.63
TINscale2	2	2.51	1410.69	0.05	1406.69
TINscale1	2	2.87	1411.05	0.04	1407.05
TIN	2	3.12	1411.30	0.04	1407.29
MAXTscale4	2	3.24	1411.42	0.04	1407.42
MAXTscale3	2	3.31	1411.49	0.03	1407.49
Null	1	4.65	1412.83	0.02	1410.83

[a] Number of parameters
[b] The difference in Akaike's Information Criterion adjusted for small samples size
[c] Akaike's Information Criterion adjusted for small sample size
[d] Akaike weights
[e] Deviance (-2*loglikelihood)

Table 2.3: means and standard deviations of 9 vegetation phenology metrics extracted at successful (n = 74) and unsuccessful nests (n = 150) of female lesser prairie-chickens marked with VHF and GPS transmitters from 2013-2015 at 3 study sites (Clark, Red Hills, and Northwest) in western Kansas.

Phenology Metric	Successful nests ($\bar{x}$, SD)	Unsuccessful nests ($\bar{x}$, SD)	*t*	DF	P
AMP	0.37 ± 0.07	0.38 ± 0.06	-0.39	129	0.70
DUR	184 ± 21	182 ± 24	0.39	168	0.70
SOST	126 ± 18	127 ± 28	-0.56	210	0.57
SOSN	0.30 ± 0.04	0.29 ± 0.04	1.20	158	0.23
MAXT*	198 ± 29	206 ± 30	-2.06	150	0.04
MAXN	0.68 ± 0.07	0.67 ± 0.07	0.36	144	0.72
EOST	309 ± 8	310 ± 15	-0.48	219	0.63
EOSN	0.32 ± 0.04	0.33 ± 0.04	-1.05	160	0.30
TIN*	0.35 ± 0.08	0.33 ± 0.07	2.00	139	0.05

*Indicates significant differences at α =0.05.

Table 2.4: means and standard deviations of 9 vegetation phenology metrics extracted at used sites of successful brood locations (n = 266) and unsuccessful brood locations (n = 55) of female lesser prairie-chickens marked with VHF and GPS transmitters from 2013-2015 at 3 study sites (Clark, Red Hills, and Northwest) in western Kansas.

Phenology Metric	Successful brood sites ($\bar{x}$, SD)	Unsuccessful brood sites ($\bar{x}$, SD)	*t*	DF	P
AMP	0.38 ± 0.06	0.37 ± 0.04	1.21	124	0.23
DUR	190 ± 14	190 ± 14	-0.25	78	0.80
SOST	119 ± 10	118 ± 11	0.82	74	0.41
SOSN	0.31 ± 0.03	0.30 ± 0.02	1.05	102	0.30
MAXT*	200 ± 33	188 ± 25	3.0	96	0.003
MAXN	0.70 ± 0.07	0.69 ± 0.04	1.38	118	0.17
EOST	309 ± 8	308 ± 8	0.69	82	0.49
EOSN*	0.34 ± 0.03	0.33 ± 0.03	2.52	73	0.01
TIN	0.38 ± 0.07	0.40 ± 0.07	-1.78	84	0.08

* Indicates significant differences at α =0.05.

Table 2.5: The mean laying dates and hatch dates (shown in both DD/MM/YYYY format and Day of Year format) of female lesser prairie-chickens marked with GPS and VHF transmitters at the Clark, Northwest, and Red Hills study sites located in western Kansas from 2013, 2014, and 2015.

	Clark			Northwest			Red Hills		
	2013	2014	2015	2013	2014	2015	2013	2014	2015
Mean laying date	N/A	4/22/2014	4/25/2015	5/7/2013	4/28/2014	4/25/2015	4/30/2013	4/29/2014	4/24/2015
Mean hatch date	N/A	5/26/2014	5/31/2015	6/9/2013	6/5/2014	6/3/2015	6/3/2013	6/19/2014	6/3/2015
Mean laying date (Day of Year)	N/A	112	115	127	118	115	120	119	114
Mean hatch date (Day of Year)	N/A	146	151	160	156	154	154	170	154

Table 2.6: The means and standard deviations of Start of Season Time (SOST) and Time of Maximum NDVI (MAXT) averaged at nest sites at 3 study sites in western Kansas (Clark, Northwest, and Red Hills) from 2013, 2014, and 2015. The Clark study site encompasses Clark county, the Northwest study site covers Logan and Gove counties, and the Red Hills study site covers Kiowa and Comanche counties. Means and standard deviations were extracted from eMODIS Remote Sensing Phenology (RSP) images and extracted values were exclusively within grasslands. Descriptions of the SOST and MAXT phenology metrics can be found in Table 2.2.

	Clark						Northwest						Red Hills					
	2013		2014		2015		2013		2014		2015		2013		2014		2015	
Phenology Metric	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
SOST	N/A	N/A	124	14	110	4	125	31	143	13	121	5	115	3	142	15	112	3
MAXT	N/A	N/A	209	15	189	34	246	21	202	13	196	32	181	34	206	19	177	34

Chapter 3 - **MODIS-based Vegetation Phenology Metrics Correlate to In-Situ Vegetation Measurements and Cattle Stocking Density**

Introduction

Grasslands are a unique but vulnerable biome that have been significantly altered since the onset of European settlement (Samson et al. 2004, Augustine et al. 2019). Historically, grassland dynamics and functions were maintained by fire, drought, and grazing, with differences in the frequency and intensity of these drivers occurring among ecoregions (Anderson 2006, Askins et al. 2007). Fire, drought, and grazing all served to control the establishment of woody species, increase grassland productivity, promote species diversity and heterogeneity, and contribute to soil quality, among other benefits in the evolution of grasslands (Askins et al. 2007). However, these ecological drivers have been significantly altered over time. There is a lack of an effective way to monitor the influence of these ecological drivers over large grassland expanses.

Fire, drought, and grazing and their interactive effects historically limited woody cover in grasslands and promoted structural and compositional heterogeneity, allowing grasslands to persist as a biome. Though all three ecological drivers are essential to grassland persistence, grazing plays a particularly unique role in the ecosystem function of grasslands. For example, grasslands grazed heterogeneously and at moderate intensities can improve plant and wildlife species diversity (Briske et al. 2008, Hovik et al. 2015, Kraft et al. 2021) and promote better soil quality compared to grasslands grazed at high intensities (Fuhlendorf et al. 2002, Waters et al. 2017, Abdalla et al. 2018). Prior to European settlement, bison (*Bison bison*) freely roamed the Great Plains by the millions, only to be driven to the brink of extinction by the late 1800s (Flores

1991, Knapp et al. 1999, Anderson 2006, Askins et al. 2007). Cattle became the dominant grazer on the landscape post-European settlement, and are the dominant contemporary grazer in grasslands. Vegetation responses to cattle are similar to those from bison (Towne et al. 2005, but see Ratajczak et al. 2022). Bison roamed freely throughout the Great Plains whereas cattle movement is restricted to pastures separated by fences, which have been considered a barrier to grassland conservation (Samson et al. 2004). Many grazing systems seek to uniformly graze multiple fenced pastures (Fuhlendorf et al. 2002, Briske et al. 2008). Variable grazing pressure within grassland or pastures with low, moderate, to high grazing intensities can create a mosaic of herbaceous plant structure and species composition. Grazing regimes such as prolonged high intensity grazing can result in increased bare ground cover, decreased proportions of forbs, and greater proportions of exotic species (Souther et al. 2019). Additionally, drought can further exacerbate negative effects of grazing (such as through the reduction of aboveground net primary productivity [Li et al. 2018]), further stressing the importance of monitoring grazing impacts across grassland-dominated landscapes.

Two such grasslands that have been altered by changes in land use and climate, resulting in a need for broad scale monitoring of ecological drivers, are the short and mixed-grass prairies of the Great Plains. These two grasslands (as well as many others) are differentiated, in part, by species composition and structure. Dominant grasses in the shortgrass prairie include blue grama (*Bouteloua gracilis*), buffalograss (*B. dactyloides*), sideoats grama (*B. curtipendula*), and hairy grama (*B. hirsuta*) that range in height from ~0.3-0.5 m (Anderson 2006). The mixed-grass prairie is comprised of both short and tall grasses such as blue grama, sideoats grama, little bluestem (*Schizachyrium scoparium*), big bluestem (*Andropogon gerardii*), western wheatgrass (*Pascopyrum smithii*), and switchgrass (*Panicum virgatum*), among others (Anderson 2006).

Aside from compositional differences, short and mixed-grass prairies can also be differentiated by their distinct Normalized Difference Vegetation Index (NDVI) profiles. The NDVI is a remotely sensed index that measures the difference between the amount of red and near infrared light being reflected from living vegetation, which provides insight into the health, vigor, and density of living vegetation (Rouse et al. 1974, Tucker 1979). This greenness index can be used to evaluate the phenological trends of vegetation, which allows researchers to differentiate among cover types using satellite data. For example, the short and mixed-grass prairies exhibit lower NDVI profiles compared to tallgrass prairies, with short grasses having the lowest seasonal NDVI trends (Paruelo and Lauenroth 1995). Additionally, NDVI can also be used to differentiate between cool-season and warm-season vegetation, with cool-season grasses reaching peak NDVI earlier than warm-season grasses (Wang et al. 2010). Aside from differentiating among land cover types, NDVI and NDVI-based remote sensing tools have widespread utility for ecological studies across many taxa.

With advancements over the last 60 years, remote sensing and remotely sensed products have become a ubiquitous tool in the arsenal of wildlife managers and researchers. Whether applied to research specific to insects (see recent advancements in Rhodes et al. 2022), fish (see an overview in Klemas 2013), ungulates, or birds (see a brief review for both birds and ungulates in Pettorelli et al. 2011), remote sensing can be successfully applied to some of the smallest and largest organisms on earth. Aside from wildlife, remote sensing is also used to evaluate ecosystem responses to disturbance, such as the response of ecosystems to fire, drought, woody encroachment, or even climate change (see a brief review in Pettorelli et al. 2005) at multiple spatial and temporal scales. For example, a collaborative remotely sensed product that is popular among researchers today is the Rangeland Analysis Platform (RAP), which incorporates NDVI data to provides estimates of percent cover of functional groups such as perennial and annual forbs and grasses, shrub, bare ground, and trees at a 30 x 30-m pixel resolution (Jones et al. 2018). Another useful remotely sensed product is the Phenology Viewer. The Phenology Viewer provides users with yearly NDVI-based products that describe the growing season phenology of vegetation (Table 3.1). Phenology metrics are calculated using MODIS imagery and are delivered at a 250-m pixel resolution. This tool allows researchers to measure changes in vegetation phenology across broad spatial and temporal scales, as well as how phenology changes in response to disturbance.

The lesser prairie-chicken (*Tympanuchus pallidicinctus*) is one of the most recently federally listed species under the Endangered Species Act, with the decision to list the northern Distinct Population Segment (DPS) as threatened and the southern DPS as endangered effective in 2023. This is a grassland-obligate species, which tend to be more sensitive to anthropogenic, climatic, and ecosystem alterations within grasslands compared to more facultative species that do not rely as heavily on grasslands among life stages (Vickery et al. 1999, Andersen and Steidl 2019, Correll et al. 2019, Londe et al. 2019). Decades-long population declines are primarily attributed to conversion of grassland to row-crop agriculture, energy and anthropogenic development, and habitat degradation (Van Pelt et al. 2013, Haukos and Zavaleta 2016). Given the uncertainty surrounding the viability of lesser prairie-chickens over the next 25 years, monitoring efforts at relevant spatial scales is more important than ever (USFWS 2021). Nearly all monitoring efforts for this species are field-based and predominantly include lek surveys (aerial and roadside) and vegetation surveys at used versus available locations. While these efforts provide managers with valuable information, they are costly, time consuming, and typically occur at small spatial scales. Given these constraints, novel methods of habitat monitoring need to be evaluated. Thus, I sought to evaluate whether field-based vegetation measurements taken within the short and mixed-grass prairies could be linked to remotely sensed vegetation phenology metrics taken from the Phenology Viewer. I also investigated whether grazing intensity within the mixed-grass prairie could be linked to remotely sensed vegetation phenology metrics. Remotely sensed products have become fairly ubiquitous in ecological research, but the use and interpretation of remotely sensed products relating to vegetation can be considered questionable without the use of ground-truthing of some sort (Turner et al. 2003, Fisher and Mustard 2007, Fontana et al. 2008).

When linking field-based vegetation data to remotely sensed phenology metrics, I predicted that phenology metrics representing season-long productivity and peak productivity would correlate most strongly to field data, given that vegetation data were collected in winter, spring, summer, and fall. I expected particularly strong correlations between measures of mean percent cover, Time Integrated NDVI (TIN; Table 3.1), and Amplitude (AMP). Time Integrated NDVI (TIN) measures the density of vegetation across the growing season and AMP measures the total increase in photosynthetic activity from the start to the peak of the growing season. I expected that greater proportions of grass cover would correlate to greater measures of TIN. I expected AMP to reflect a similar relationship because if there are greater proportions of grass cover at a site, there should be a greater increase in photosynthetic activity to reflect greater amount of cover. Additionally, I expected negative correlations between mean litter cover and depth measurements and AMP, TIN, and Maximum NDVI (MAXN). Litter cover is not measured by NDVI, so I expected negative correlations that would depict the lack of living cover.

Few studies have linked grazing to changes in remotely sensed vegetation phenology, but there are those that have identified phenological differences due to grazing (Giralt-Rueda and Santamaria 2021, Balata et al. 2022, Snyder et al. 2023). Given the dynamic ways in which grazing can affect grassland ecosystems and the species that depend on them, understanding whether remotely sensed differences can be measured within pastures is useful. Because Clark County, Kansas, is predominantly used for cattle production and supports populations of lesser prairie-chickens, I was interested in how phenology metrics might vary with stocking densities. When linking vegetation phenology metrics to different stocking density, I predicted that pastures with greater cattle stocking density would vary in maximum NDVI and TIN. Bradley and O'Sullivan (2011) found that NDVI was lower within a 500-m radius of grazing sheep, but this effect did vary based on land use, elevation, and stocking rate. Grazing reduces plant biomass and vertical cover, resulting in less cover and therefore less total photosynthetic materials. Therefore, I expected that remotely sensed vegetation phenology metrics that measure vegetation density, peak productivity, and season-long productivity would correlate negatively with increased stocking density.

Methods

Study area

My study area was the result of pooled data previously collected in portions of western Kansas. The study area covers two of the four ecoregions occupied by the lesser prairie-chicken: the Mixed-Grass Prairie and the Short-Grass Prairie/CRP Mosaic (Figure 3.1; McDonald et al. 2014, Boal and Haukos 2016). Fire, grazing, and precipitation/drought events are historical ecological drivers across this range, though all of these regimes have shifted in frequency and intensity over the last 100 years (Askins et al. 2007). Drought specifically is a common disturbance that is predicted to increase in frequency and intensity as climate change progresses (Strzepek et al. 2010, Grisham et al. 2016). Throughout the lesser prairie-chicken distribution, there is also a distinct longitudinal mean annual precipitation gradient from east to west as well as variability in annual precipitation and aboveground net primary productivity (Sala et al. 1988). In the easternmost portion of the LEPC range, average annual precipitation ranges between 63.9 and 76.3 cm (Grisham et al. 2016). In the westernmost portions of the LEPC range, average annual precipitation ranges between 27.8 and 40.5 cm (Grisham et al. 2016).

Within the Mixed-Grass Prairie Ecoregion, there were 2 study sites: Clark (located in Clark County) and Red Hills (located in Kiowa and Comanche counties). The Red Hills study site was located in the easternmost portion of the LEPC range, receives greater annual precipitation compared to other sites, and is managed using rotational and patch-burn grazing, whereas properties on the Clark Site were typically managed with low intensity rotational grazing. Soil composition in the Red Hills was mostly sandy loam, clay loam, and clay; soil composition in the Clark County study site was primarily fine sandy loams, fine sands, and loamy fine sands (Sullins et al. 2018). Dominant vegetation across both study sites included grasses such as little bluestem, sand dropseed (*Sporobolus cryptandrus*), alkali sacaton (*Sporobolus airoides*), blue grama, big bluestem, switchgrass, and sideoats grama. Abundant forbs included western ragweed (*Ambrosia psilostachya*), kochia (*Kochia scoparium*), Russian thistle (*Salsola* sp.), broomweed (*Amphiachyris dracunculoides*), broom snakeweed (*Gutierrezia sarothrae*), and Louisiana sagewort (*Artemisia ludiviciana*). Common shrubs included sand sagebrush (*Artemisia filifolia*), sand plum (*Prunus angustifolia*), eastern redcedar (*Juniperus* *virginiana*), and fragrant sumac (*Rhus aromatia*; Sullins et al. 2018, Gulick 2019, Lautenbach et al. 2019).

Within the Short-Grass Prairie/Conservation Reserve Program (CRP) Mosaic Ecoregion, there was one study site labeled the Northwest study site, which encompassed Logan and Gove counties. Although this site was predominantly short-grass prairie, the inclusion of CRP grasslands, which are typically not grazed, provided both mixed and short grasses in this region which are typically not grazed. Dominant land uses in the Northwest study area includes grazing, CRP grasslands, and row-crop agriculture. Dominant grasses included blue and hairy grama, little bluestem, buffalograss, big bluestem, sideoats grama, and western wheatgrass. Common forbs included Russian thistle, western ragweed, broom snakeweed, annual buckwheat, prairie sunflower (*Helianthus petiolaris*), and nine-anther dalea (*Dalea enneandra*). Dominant shrubs included sand sagebrush and yucca (Sullins et al. 2018, Lautenbach et al. 2019).

Vegetation measurements: nest, brood, and patch vegetation

From 2013-2015, I collected vegetation data from January through December at nest sites and paired random points, brood sites and paired random points, used points (visited by marked lesser prairie-chickens), and random points across study areas. To generate non-paired random points, I used the “Create Random Point” tool in ArcGIS. With this tool, I specified that 10 random points would be generated in each patch at all study areas. When collecting vegetation data at used sites, I randomly selected 2 points per week for each bird. Nest vegetation surveys were conducted at the nest site within a week of nest fate determination, and brood vegetation surveys were conducted at locations used by brooding females. Paired random points were located within 300-m of used sites.

The same protocol was followed for vegetation data collection at all points. At the center of each point, a Robel pole (Robel et al. 1970) and a 60 x 60-cm Daubenmire frame were placed on the ground. At point center, the following data were collected including height of tallest vegetation (cm) within a modified 60 cm x 60 cm Daubenmire frame. I then identified species, height, and distance to point center for nearest grass, forb, and shrub. I estimated percent canopy cover of shrub, forbs, bare ground, grass, and litter; and measured litter depth at the northwest corner of the modified Daubenmire frame. I repeated these same measurements 4 m from the point center in each cardinal direction. In addition to these measurements, 0%, 25%, 50%, 75%, and 100% visual obstruction readings in dm were taken in each cardinal direction (Robel et al. 1970).

Remotely sensed data collection

To determine whether remotely sensed phenology metrics can be linked to ground-based vegetation data, I used imagery from the Aqua Moderate Resolution Imaging Spectroradiometer (hereafter MODIS) satellite. Specifically, I used a product derived from MODIS images termed the C6 Aqua Western 250 m eMODIS RSP (remote sensing phenology) imagery, with 250 m representing the pixel resolution (Jenkerson et al. 2010, Brown et al. 2015). Phenology metric data were maintained and processed yearly by the USGS Earth Resources Observation and Science (EROS) Center. Input data used by EROS to develop these phenology products are weekly eMODIS maximum NDVI composites that are temporally smoothed (Jenkerson et al. 2010). In total, EROS develops 9 vegetation phenology metrics that cover the contiguous United States (Table 3.1). For this study, I used phenology data from the western United States extent, as all study areas were within this extent.

Typically, eMODIS images are ready for immediate use following download. However, it was necessary to conduct additional pre-processing before conducting any analyses. This was due to the presence of cells comprised of water and “No Data” cells where the phenology metric was unable to be calculated. Cells containing water are assigned a value of 255 or 1000. Similarly, cells where phenology metrics were unable to be calculated were assigned a value of either 0 or -1000. These values, if included in analyses, would have potentially led to inaccurate results. To account for this, I converted any cells with values of 255, 0, 1000, or -1000 to true “No Data” cells using the “Set Null” function in ArcGIS 10.8.

Linking vegetation measurements and stocking density to phenology metrics:

To evaluate linkages among phenology measurements and on-the-ground vegetation measurements taken at nest, brood, and random points, I performed multiple correlation analyses in Program R (Table 3.1). First, I separated vegetation data by year (2013, 2014, 2015). Given that I was using vegetation data that spanned the entire year, I decided that phenology metrics representing season-long growth as well as cumulative and peak biomass would be the most appropriate to evaluate potential correlations. Of the 9-phenology metrics that I have access to, 3 describe season-long growth pattern or peak and cumulative biomass: Amplitude (AMP), Maximum NDVI (MAXN), and Time Integrated NDVI (TIN). In ArcGIS 10.8, I imported the 3 phenology rasters (AMP, MAXN, and TIN) and imported the point vegetation data as a shapefile. I used the “Extract Multi Value to Point” tool to extract phenology values at all point locations. Following this, I used the “cor” function in Program R to evaluate Pearson correlation coefficients between AMP, MAXN, and TIN with average grass, forb, shrub, bare ground, and litter cover, average litter depth, and average visual obstruction readings at 100%, 75%, 50%, 25%, and 0% visual obstruction (Rodgers and Nicewander 1988). I then evaluated associated p-values (α = 0.05) to determine which phenology metrics were significantly correlated with vegetation measures.

To examine correlations between phenology metrics and cattle stocking density, I obtained data on pasture area and animal units (e.g., mature cattle or cow plus calf <6 months of age) on the Gardiner ranch in Clark County, Kansas. Stocking density was derived by animal units by pasture area (AU/ha). I then imported pasture data into ArcGIS 10.8 as polygons. I used 9 phenology metrics for grazing correlation analyses. I imported all phenology rasters into ArcGIS 10.8 and clipped them to the Gardiner ranch pastures. To extract phenology metrics based on cattle stocking density, I converted the pasture polygons into rasters using the "Polygon to Raster" tool. Finally, I converted the pasture rasters into points using the "Raster to Point" tool and carried over the stocking density field. I used the "Extract Multi-Values to Point" tool to extract phenology metrics based on stocking density. In Program R, I evaluated correlations using the Pearson's correlation coefficient between each of the 9 phenology metrics and stocking densities and evaluated p-values to determine which correlations were significant (α = 0.05; Rodgers and Nicewander 1988).

Results

Linking ground-based vegetation measurements to remotely sensed vegetation phenology metrics

I had access to vegetation data collected in 2013 (n = 2,606), 2014 (n = 6,915), and 2015 (n = 5,593). I included vegetation data from January to December each year to match the yearlong measures of phenology metrics. In 2013, vegetation phenology metrics were correlated with several field-based vegetation measures. Notably, AMP, MAXN, and TIN were each positively correlated to all average VO measures (r = 0.13 – 0.31; Figure 3.2). Aside from VO, AMP was positively correlated with grass (r = 0.06), forb cover (r = 0.16), and litter depth (r = 0.07). As expected, AMP was negatively correlated with bare ground cover (r = -0.15). However, some of these correlations, despite significance at $P < 0.05$, were weak. For example, the correlation between AMP and average grass cover was weak (r = 0.06, $P = 0.004$), as was the positive correlation between AMP and litter depth (r = 0.07, $P = 0.0003$). The negative correlation between AMP and average shrub cover was also weak (r = -0.04, $P = 0.03$). MAXN was also positively correlated with forb cover. MAXN was negatively correlated with grass (r = -0.06, $P = 0.001$) and shrub cover (r = -0.04, $P = 0.05$). Last, TIN was positively correlated with forb cover (r = 0.51). Negative correlations with TIN included bare ground cover (r = -0.11), grass cover (r = -0.17), and litter depth (r = -0.09).

In 2014, AMP was positively correlated, albeit weakly, with average VO at 75%, 50%, and 25% obstruction (r= 0.02 – 0.03, Figure 3.3). AMP was also positively correlated with grass cover (r = 0.13) and litter depth (r = 0.03). Significant negative correlations occurred between AMP and VO at 0% obstruction (r = -0.10), bare ground cover (r = -0.07), forb cover (r = -0.05), and litter cover (r = -0.04). Positive correlations were found between MAXN and average VO at 50% and 25% obstruction (r = 0.04 – 0.06), and grass cover (r = 0.16). Significant negative correlations were seen between MAXN and average VO at 0% obstruction (r = -0.15), litter depth (r = -0.08), bare cover (r = -0.06), forb cover (r = -0.03), litter cover (r = -0.15), and shrub cover (r = -0.02). Last, TIN was positively correlated with average VO at 100%, 75%, 50%, and 25% obstruction (r = 0.03 – 0.07), as well as grass cover (r = 0.13). TIN was negatively correlated with VO at 0% obstruction (r = -0.09), bare ground cover (r = -0.05), forb cover (r = -0.05), and litter cover (r = -0.10).

In 2015, AMP was positively correlated with average VO at 100% and 75% obstruction (r = 0.03 – 0.05), as well as grass cover (r = 0.07; Figure 3.4). Conversely, AMP was negatively correlated with bare cover (r = -0.11) and shrub cover (r = -0.05). Positive correlations occurred between MAXN and all average VO measures (r = 0.06 – 0.11), as well as forb cover (r = 0.22). Negative correlations occurred between MAXN and litter depth (r = -0.11), and bare ground (r = -0.09), litter (r = -0.14), and shrub cover (r = -0.08). Last, significant positive correlations occurred between TIN and forb cover (r = 0.22) as well as all measures of VO (r = 0.10 – 0.14). Significant negative correlations occurred between TIN and litter depth (r = -0.09), bare ground (r = -0.08), and litter cover (r = -0.22).

Linking stocking density to vegetation phenology metrics:

In 2014, 4 of the 9 vegetation phenology metrics were correlated with stocking density in 62 pastures in Clark County, Kansas (Figures 3.5, 3.6). Positive correlations occurred between stocking density, AMP (r = 0.07), and TIN (r = 0.13). Significant negative correlations occurred between stocking density and SOSN (r = -0.12) and EOSN (r = -0.05).

In 2015, 4 of the 9 vegetation phenology metrics were correlated with stocking density (Figure 3.7). The only positive correlation to occur was between stocking density and SOSN (r = 0.12), which increased with stocking density. The remaining significant correlations were negative and occurred between stocking density, TIN (r = -0.17), EOST (r = -0.05), and DUR (r = -0.05). As stocking density decreased, values of TIN and EOST increased (Figure 3.8).

Discussion

Minimal, if any, efforts have been made to link in-situ vegetation measurements or stocking density to broad-scale remotely sensed vegetation products. The results of such analyses would inform vegetation monitoring efforts important for lesser prairie-chickens and other grassland wildlife. My research provides evidence that remotely sensed vegetation phenology at the 250-m scale metrics do correlate, both strongly and weakly, to in-situ vegetation measurements, with measures of percent cover and visual obstruction more consistently correlated with phenology metrics. Similarly, I also provided evidence that remotely sensed vegetation phenology metrics correlated with year-long stocking densities on a private ranch in Clark County, Kansas. While specific correlations with phenology metrics, in-situ vegetation measurements, and stocking densities were significant each year, most correlations varied among years, in that correlations that were statistically significant one year were not necessarily significant the following year. Many factors could be contributing to interannual variability of phenological correlations including amount and timing of precipitation, temperature, land use, and lag effects; all of which were not evaluated in my research. Importantly, TIN is one metric that was significantly correlated with in-situ vegetation measurements and stocking density each year. The TIN metric was important in predicting nest site-selection and brood-rearing habitat abundance (Chapter 1). It appears that TIN is most consistently related NDVI-derived metric of habitat use for lesser prairie-chickens. There is also utility in using it for remote monitoring of lesser prairie-chicken habitat, as indicated by its correlations with stocking density and in-situ vegetation measurements.

Linking ground-based vegetation measurements to remotely sensed vegetation phenology metrics:

Overall, I was able to confirm some of my predictions regarding correlations between phenology metrics and in-situ vegetation measurements. The metrics that were most strongly correlated to in-situ vegetation measurements were TIN and MAXN, whereas correlations between vegetation measurements and AMP tended to be weaker. The strongest correlations between vegetation measurements and phenology consistently occurred with measures of mean percent cover of grass and forb cover. Grass and forb cover are, naturally, the dominant cover types in grasslands and I observed greater proportions of these functional groups compared to others (Kraft et al. 2021). Additionally, eMODIS satellite imagery is taken at nadir, meaning that images are taken directly below the instrument. As a result, images are capturing the overhead density of horizontal cover. In my analyses, percent cover was indicated by the 250-m eMODIS images, which is logical given the angle of image capture.

In terms of specific correlations, TIN was the phenology metric that most consistently correlated with vegetation measurements, with the strongest correlations seen with forb cover and 50% visual obstruction in 2013. AMP and MAXN typically had similar correlations as TIN, for which phenology metrics increased with measurements of herbaceous vegetation and visual obstruction and decreased with bare ground and litter measurements. In addition to TIN, MAXN was a fairly strong predictor of forb cover in 2013 and 2015 and all predictions of visual obstruction in 2013. All other significant correlations had r values < 0.2, suggesting that using higher resolution remotely sensed phenology metrics that better align with the scale of in-situ measurements or combining multiple phenology metrics could be beneficial. Most weak correlations occurred between litter depth, shrub cover, and, in 2014 and 2015, specific average VOR measures.

Weak negative correlations between shrub cover and phenology may be reflective of low prevalence of shrubs at evaluated locations or a result of the deciduous nature of sand sagebrush and other shrubs in our study area (e.g., sand plum and fragrant sumac). Phenology metrics can be used to predict shrublands that tend to exhibit lower NDVI values compared to grasslands (Paruelo and Lauenroth 1995). In mixed-grass and short-grass prairies, percent shrub cover at nest sites is quite low compared to other cover types, with 1.31% in the mixed-grass prairie and 1.96% in the short-grass prairie (Hagen et al. 2013). Relatedly, there may simply be a lower proportion of shrubs in the 250-m around used sites in general within the ecoregions evaluated (e.g., mixed-grass prairie, and short-grass prairie). In the sand sagebrush and sand shinnery oak prairies, proportion of shrub cover is much higher across the landscape, which may lead to better correlation with phenology metrics. This would make shrub cover extremely unlikely to be reflected in the coarse phenology images, which may be explaining this weak relationship since grasslands are the dominant cover type used by lesser prairie-chickens in the short and mixed-grass prairies. It appears phenology metrics cannot be reliably linked to shrub cover at this time or at the 250-m scale in short and mixed-grass prairies.

Forb cover exhibited particularly strong correlations with TIN, MAXN, and AMP in 2013 and 2015, but not in 2014. Interestingly, in years with correlations between phenology and forb cover, correlations with mean grass cover were considerably weaker, which warrants additional analyses. For example, in 2014, grass cover was correlated with phenology while forb cover was either weakly correlated or not significantly correlated at all. In general, TIN, MAXN, and AMP reflected increased proportions of grass and forb cover. The inverse relationship between grass and forb cover, however, is interesting and in 2014 this may be a product of an eruption of forbs following the intense drought in 2012 and 2013 (Hoerling et al. 2014). In future analyses, it may be more useful to combine mean cover of grass and forbs into one category and to include some measure of drought severity. The Rangeland Analysis Platform combines forbs and grasses instead of measuring them separately, and Laliberte et al. (2010) were unable to distinguish forbs from grasses using Unmanned Aerial Vehicle (UAV) imagery, leading them to also combine those two groups into one. Given the coarse 250-m resolution of the eMODIS RSP images used in my analysis and the finer scale at which vegetation measures are being taken, it may be understandably difficult to differentiate between the two cover types. If I were to combine forb and grass cover, I would expect a consistently strong significant correlation to occur.

Additionally, TIN and MAXN were negatively correlated with measures of litter cover and depth in 2014 and 2015. Phenology metrics are based on NDVI, which measures the difference between the amount of red and near infrared light being reflected from living vegetation. Litter is, by definition, dead and residual cover and therefore not measured by NDVI-based metrics. This is why I expected a negative correlation between NDVI-based phenology metrics and litter cover. Additionally, negative correlations between litter cover, MAXN, and TIN were largest in 2015. In 2015, low grazing intensity matched with favorable precipitation two years post-drought allowed for buildup of litter cover (D. S. Sullins, Kansas State University, personal communication).

Last, correlations between vegetation measurements and phenology metrics occurred between VO at multiple percentages of cover (e.g., 0%, 25%, 50%, 75%, 100% obstruction). Correlations between AMP and MAXN and VO occurred at specific percent obstructions; TIN was the only variable to be correlated with every measure of VO each year. Unlike percent cover, visual obstruction measures the vertical density of vegetation. As aforementioned, eMODIS satellite images are getting a more direct measure of horizontal cover rather than vertical structure. However, if vegetation is dense from the standpoint of VO, it is likely dense from a horizontal cover perspective as well, which might explain consistent correlations with TIN among years.

Linking stocking density to remotely sensed vegetation phenology metrics:

In the grassland landscape occupied by lesser prairie-chickens in the short and mixed-grass prairies, cattle grazing is one of most dominant land uses. Effects of grazing vary temporally and spatially and interact with other drivers such as drought and fire, making effects of grazing interannually variable. While grazing strategies such as patch burn are effective for maintaining the structural heterogeneity that benefit lesser prairie-chickens across life stages (Gulick 2019, Lautenbach et al. 2021, Kraft et al. 2021), these systems are infrequently implemented within the study areas due to a number of socio-economic and cultural reasons that still prevail in current times (Adhikari et al. 2023). In the Great Plains (including the study areas), variable grazing regimes range from low, moderate, to high stocking densities exist, with temporal variation in the duration of grazing within a pasture. This variability in grazing intensity and duration, particularly during drought years, can have significant effects on vegetation, which may or may not be to the detriment of lesser prairie-chicken habitat (Kraft et al. 2021). Now that the lesser prairie-chicken is officially listed under the Endangered Species Act, the ability to understand how one of the most dominant land uses across the Great Plains is affecting lesser prairie-chicken habitat at broad spatial scales is extremely important for future management.

Overall, correlations between stocking density and phenology metrics were from metrics that measure cumulative productivity (AMP, DUR) and total aboveground biomass (TIN), as well as start and end of growing season metrics (SOSN, EOSN, EOST). Interestingly, TIN was correlated to stocking density in 2014 and 2015, but the direction of correlation switched. In 2014, TIN was positively correlated with stocking density. Whereas in 2015, TIN was negatively correlated with stocking density. This correlation was driven by very high stocking densities in a few small pastures. In 2014, the largest stocking density was 0.56 and occurred in a pasture that was 57 ha (141 acres), which is quite small compared to other pastures on the ranch that typically exceed 607 ha (1,500 acres). Cattle grazed this pasture from 8/8/2014 until 10/10/2014. Therefore, the vegetation in this pasture experienced no cattle grazing during most of the growing season, allowing vegetation to grow with minimal biomass removal. Additionally, with drought conditions occurring in 2013, vegetation may have been responding positively to much-needed precipitation in 2014, which also would have stimulated growth (NOAA 2023).

In 2015, however, two pastures appear to be driving the negative relationship between TIN and stocking density (Figure 3.7). The largest stocking density occurred in a pasture that was only 27 ha (67 acres). Similarly, the second largest stocking density (0.68) occurred in a pasture that was 29 ha (73 acres). Although high intensity grazing only occurred from May until July in the smallest pasture, it is highly likely that this pasture simply lacked the density of vegetation needed to support such a high stocking rate of cattle. Vegetation that is subjected to high intensity grazing can experience large reductions in biomass and tend to be more homogeneous (Fuhlendorf and Engle 2001). The reduction in biomass associated with high grazing intensities was evident in the negative relationship between TIN and stocking density. Of all the phenology metrics, TIN is the metric that is used as a proxy for the density of vegetation cover (Potter 2020, Potter and Alexander 2020). Thus, my research indicates that high-intensity grazing results in less vegetation cover, which is a relationship that can be monitored remotely.

Aside from season-long measures of productivity, correlations also occurred with specific phenological occurrences. Specifically, EOSN and EOST were lower and earlier in pastures with greater stocking density, indicating plants do not have the same capacity for regrowth as they did earlier in the season at greater grazing intensities (Trlica 2013), which can result in lower than normal vigor prior to the onset of senescence (Trlica 2013). The fact that NDVI and the date of the end of the growing season were negatively correlated with increased stocking rates suggests high intensity cattle grazing influences vegetation across the growing season leading into dormancy, and that high stocking densities can result earlier end of the growing season dates and values of NDVI. Alternatively, research in Nevada meadows has shown that high intensity grazing does not affect the growing season (Richardson et al. 2021). As mentioned, correlations between stocking density and EOSN and EOST are weak. While it is possible that increased grazing pressure is affecting end of the growing season phenology, there is also a chance that these results are negligible.

My results provide basic inference into the effects of cattle stocking density on remotely sensed vegetation phenology. Correlations were based on pixels within 62 pastures in Clark County, Kansas; therefore representing a very small percentage of the lesser prairie-chicken range and the Great Plains in general. Where possible, it would be beneficial to conduct these same correlation analyses on additional pastures to determine if phenology is reflecting the effects of grazing in more than one ecoregion. Additionally, it is worth noting that precipitation, soil type, temperature, etc. also affect vegetation phenology and productivity in tandem with grazing, especially at broad spatial scales. Thus, it is possible that inferences from these correlations may be relatively limited. Ultimately, however, the fact that vegetation phenology metrics are correlated to stocking density indicates that there is utility in using remotely sensed vegetation phenology metrics to monitor the effects of grazing on vegetation

Conclusions

The importance of monitoring changes in habitat availability for threatened and endangered species at relevant spatial scales cannot be understated. Habitat loss and degradation are the primary reasons for lesser prairie-chicken population declines, yet managers have no effective way to monitor lesser prairie-chicken habitat and any changes that may occur at relevant broad spatial scales. Currently, the primary method of evaluating habitat is through the collection of field-based vegetation measurements at used and random locations. Vegetation surveys are often conducted at fine spatial scales (4 m) and over short temporal scales. Field-based monitoring alone is not feasible given the time, personnel, and financial components of such an undertaking, combined with the uncertain viability of this species over the next 25 years (USFWS 2021). Fortunately, remotely sensed phenology products appear to hold promise for accomplishing broad-scale habitat monitoring for threatened species such as the lesser prairie-chicken. My research is the first attempt to link stocking density and field-based measurements to vegetation phenology for the purpose of lesser prairie-chicken habitat conservation; results seem promising. The 250-m spatial scale at which the phenology metrics are delivered may be coarse, but they are effective at relating to certain ground measurements and the effects of stocking density.

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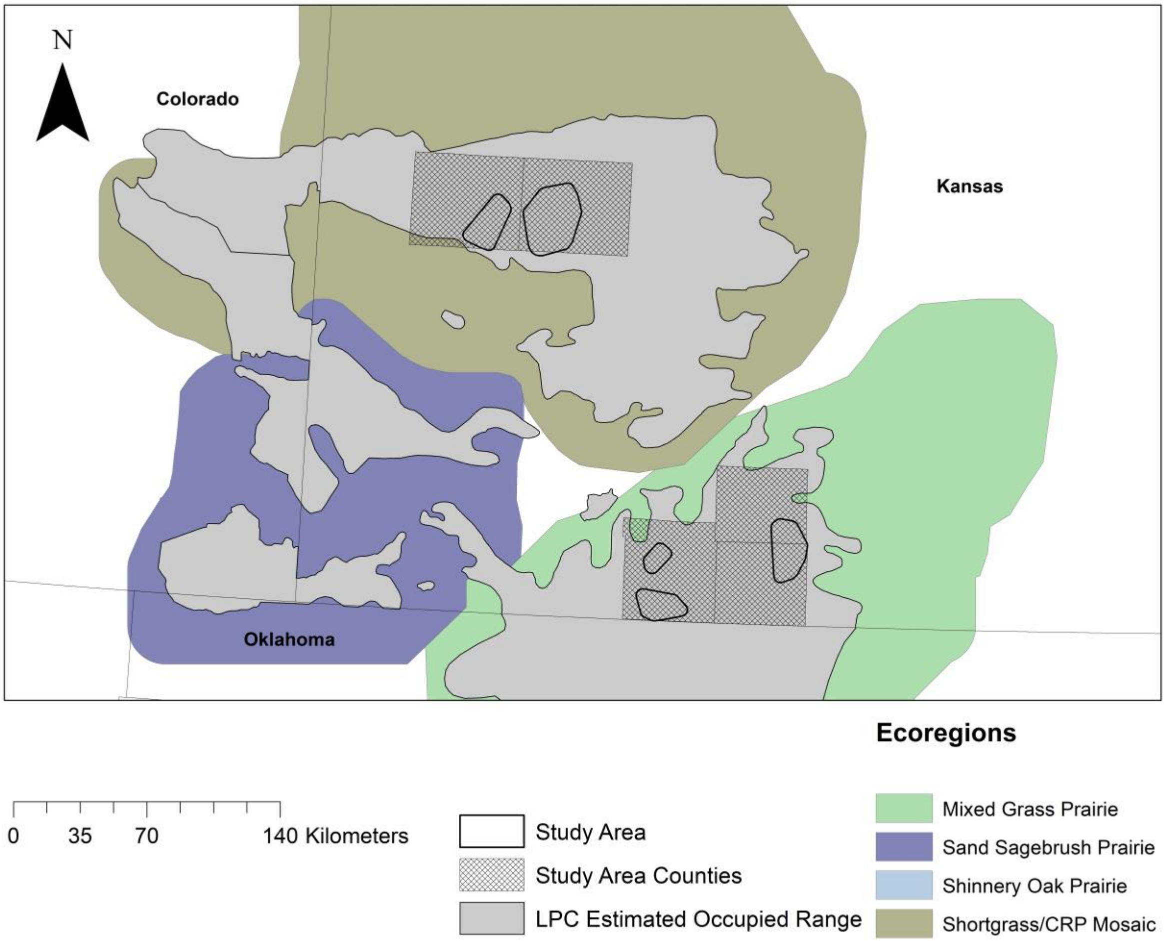
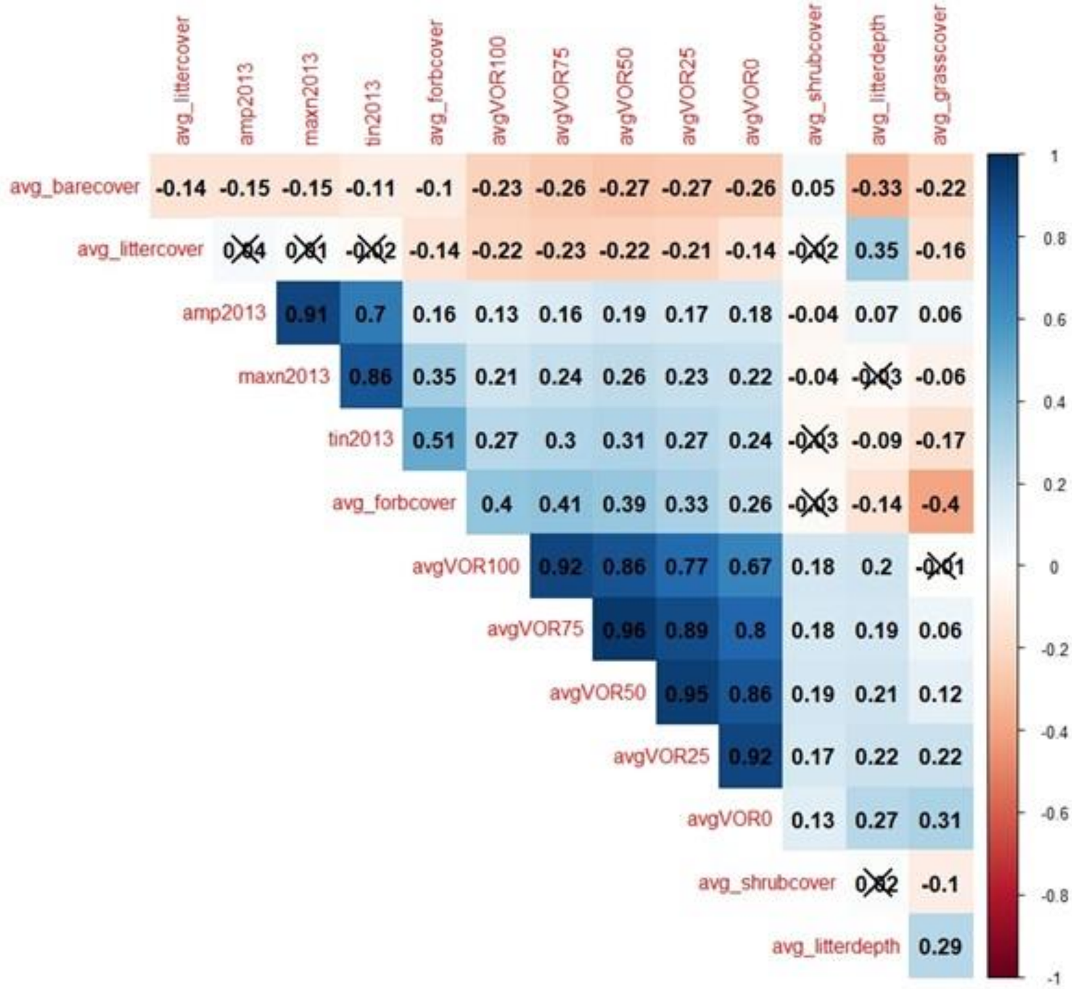
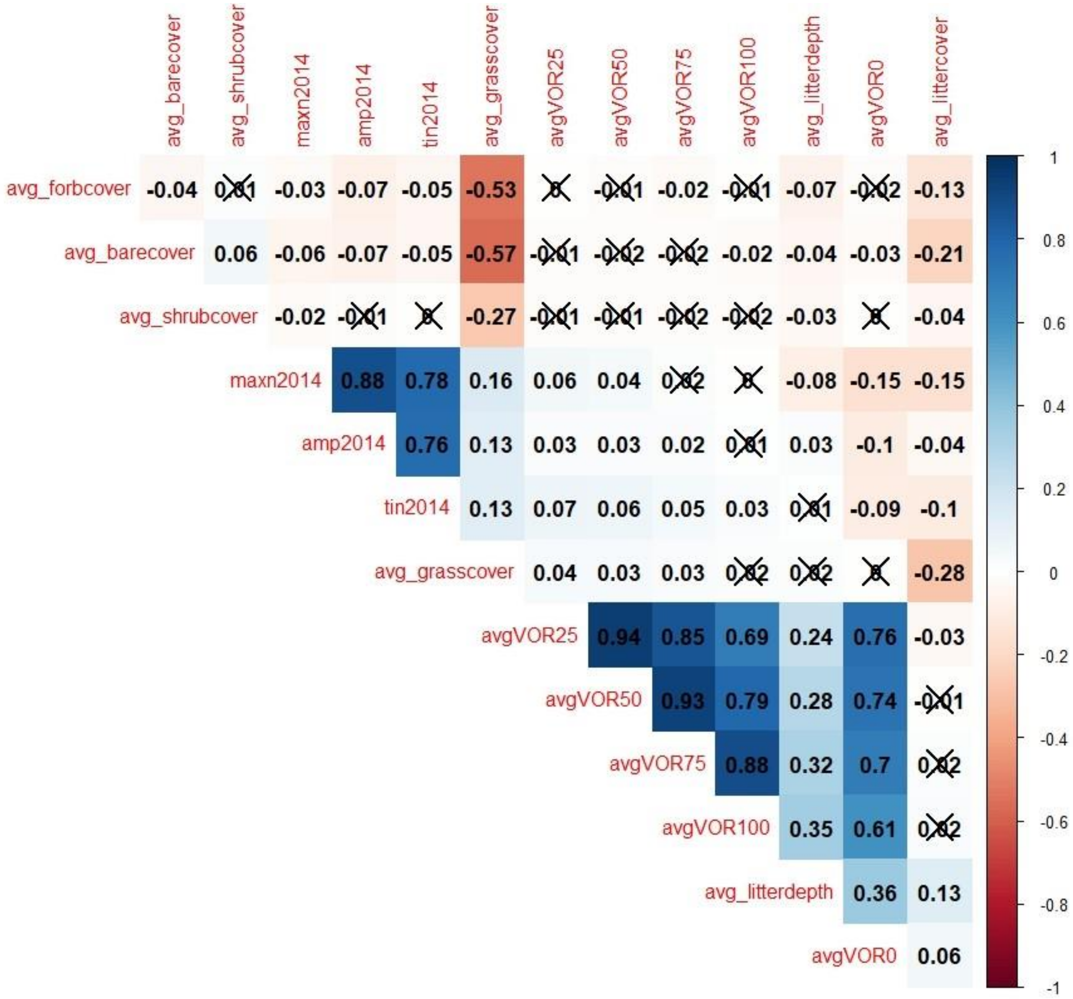


Figure 3.1: Map of the study area (Red Hills, Northwest, and Clark) covering Logan, Gove, Clark, Kiowa, and Comanche counties. Study areas are located within the Mixed-Grass and Short-Grass/Conservation Reserve Program (CRP) Mosaic of the lesser prairie-chicken range in western Kansas.



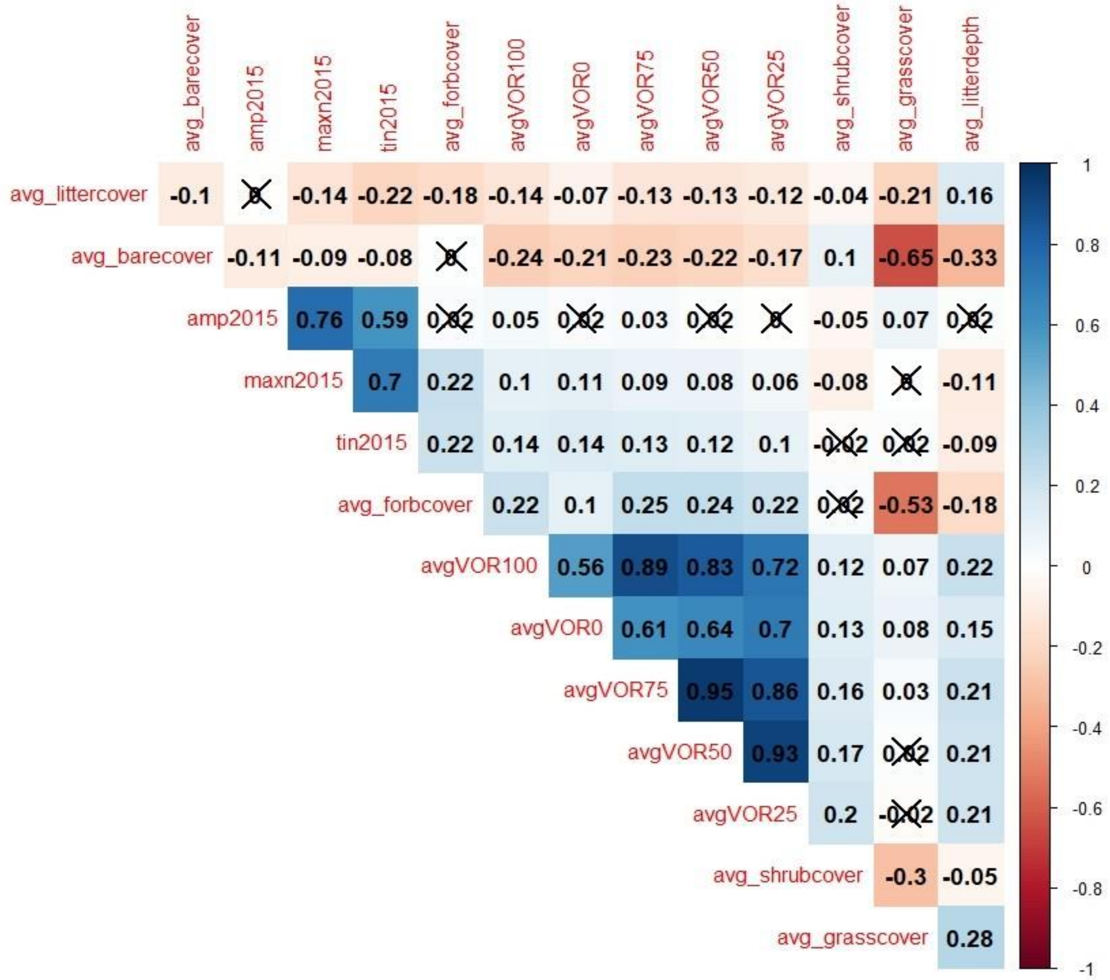
	avg_littercover	amp2013	maxn2013	tin2013	avg_forbcover	avgVOR100	avgVOR75	avgVOR50	avgVOR25	avgVOR0	avg_shrubcover	avg_litterdepth	avg_grasscover
avg_barecover	-0.14	-0.15	-0.15	-0.11	-0.1	-0.23	-0.26	-0.27	-0.27	-0.26	0.05	-0.33	-0.22
avg_littercover		0.04	0.01	-0.02	-0.14	-0.22	-0.23	-0.22	-0.21	-0.14	-0.02	0.35	-0.16
amp2013			0.91	0.7	0.16	0.13	0.16	0.19	0.17	0.18	-0.04	0.07	0.06
maxn2013				0.86	0.35	0.21	0.24	0.26	0.23	0.22	-0.04	-0.03	-0.06
tin2013					0.51	0.27	0.3	0.31	0.27	0.24	-0.03	-0.09	-0.17
avg_forbcover						0.4	0.41	0.39	0.33	0.26	-0.03	-0.14	-0.4
avgVOR100							0.92	0.86	0.77	0.67	0.18	0.2	-0.01
avgVOR75								0.96	0.89	0.8	0.18	0.19	0.06
avgVOR50									0.95	0.86	0.19	0.21	0.12
avgVOR25										0.92	0.17	0.22	0.22
avgVOR0											0.13	0.27	0.31
avg_shrubcover												0.02	-0.1
avg_litterdepth													0.29

Figure 3.2: Correlation matrix of vegetation measurements (n = 2,606) and 3 vegetation phenology metrics calculated in 2013 by the USGS Earth Resources Observation and Science Center (EROS). Vegetation measures were taken in 2013 at nest, brood, and random locations in Clark, Kiowa, Comanche, Logan, and Gove counties in Kansas, USA. Vegetation measures were collected in 4 m radius plots and included visual obstruction (VOR) at 100%, 75%, 50%, 25%, and 0%, average percent cover of grass, forbs, bare ground, shrub, and litter, and the mean of 32 litter depth measurements. Phenology metrics included in the correlation analysis were Time Integrated NDVI (TIN), Maximum NDVI (MAXN), and Amplitude (AMP). Values displayed in the matrix squares represent r values derived from the Pearson correlation coefficient. Correlation matrix squares with x's through them represent non-significant (*P* > 0.05) correlations.



	avg_barecover	avg_shrubcover	maxn2014	amp2014	tin2014	avg_grasscover	avgVOR25	avgVOR50	avgVOR75	avgVOR100	avg_litterdepth	avgVOR0	avg_littercover
avg_forbcover	-0.04	~~0.01~~	-0.03	-0.07	-0.05	-0.53	~~0~~	~~-0.01~~	-0.02	~~-0.01~~	-0.07	~~-0.02~~	-0.13
avg_barecover		0.06	-0.06	-0.07	-0.05	-0.57	~~-0.01~~	~~-0.02~~	~~-0.02~~	-0.02	-0.04	-0.03	-0.21
avg_shrubcover			-0.02	~~-0.01~~	~~0~~	-0.27	~~-0.01~~	~~-0.01~~	~~-0.02~~	~~-0.02~~	-0.03	~~0~~	-0.04
maxn2014				0.88	0.78	0.16	0.06	0.04	~~0.02~~	~~0~~	-0.08	-0.15	-0.15
amp2014					0.76	0.13	0.03	0.03	0.02	~~0.01~~	0.03	-0.1	-0.04
tin2014						0.13	0.07	0.06	0.05	0.03	~~0.01~~	-0.09	-0.1
avg_grasscover							0.04	0.03	0.03	~~0.02~~	~~0.02~~	~~0~~	-0.28
avgVOR25								0.94	0.85	0.69	0.24	0.76	-0.03
avgVOR50									0.93	0.79	0.28	0.74	~~-0.01~~
avgVOR75										0.88	0.32	0.7	~~0.02~~
avgVOR100											0.35	0.61	~~0.02~~
avg_litterdepth												0.36	0.13
avgVOR0													0.06

Figure 3.3: Correlation matrix of vegetation measurements (n = 6,915) and 3 vegetation phenology metrics calculated in 2014 by the USGS Earth Resources Observation and Science Center (EROS). Vegetation measures were taken in 2014 at nest, brood, and random locations in Clark, Kiowa, Comanche, Logan, and Gove counties in Kansas, USA. Vegetation measures were collected in 4 m radius plots and included visual obstruction (VOR) at 100%, 75%, 50%, 25%, and 0%, percent cover of grass, forbs, bare ground, shrub, and litter, and the mean of 32 litter depth measurements. Phenology metrics included in the correlation analysis are Time Integrated NDVI (TIN), Maximum NDVI (MAXN), and Amplitude (AMP). Values displayed in the matrix squares represent *r* values derived from the Pearson correlation coefficient. Correlation matrix squares with x's through them represent non-significant (*P* > 0.05) correlations.



	avg_barecover	amp2015	maxn2015	tin2015	avg_forbcover	avgVOR100	avgVOR0	avgVOR75	avgVOR50	avgVOR25	avg_shrubcover	avg_grasscover	avg_litterdepth
avg_littercover	-0.1	0	-0.14	-0.22	-0.18	-0.14	-0.07	-0.13	-0.13	-0.12	-0.04	-0.21	0.16
avg_barecover		-0.11	-0.09	-0.08	0	-0.24	-0.21	-0.23	-0.22	-0.17	0.1	-0.65	-0.33
amp2015			0.76	0.59	0.02	0.05	0.02	0.03	0.02	0	-0.05	0.07	0.02
maxn2015				0.7	0.22	0.1	0.11	0.09	0.08	0.06	-0.08	0	-0.11
tin2015					0.22	0.14	0.14	0.13	0.12	0.1	-0.02	0.02	-0.09
avg_forbcover						0.22	0.1	0.25	0.24	0.22	0.02	-0.53	-0.18
avgVOR100							0.56	0.89	0.83	0.72	0.12	0.07	0.22
avgVOR0								0.61	0.64	0.7	0.13	0.08	0.15
avgVOR75									0.95	0.86	0.16	0.03	0.21
avgVOR50										0.93	0.17	0.02	0.21
avgVOR25											0.2	-0.02	0.21
avg_shrubcover												-0.3	-0.05
avg_grasscover													0.28

Figure 3.4: Correlation matrix of vegetation measurements (n = 5,593) and 3 vegetation phenology metrics calculated in 2015 by the USGS Earth Resources Observation and Science Center (EROS). Vegetation measures were taken in 2015 at nest, brood, and random locations in Clark, Kiowa, Comanche, Logan, and Gove counties in Kansas, USA. Vegetation measures included mean visual obstruction (VOR) at 100%, 75%, 50%, 25%, and 0%, percent cover of grass, forbs, bare ground, shrub, and litter, and the mean of 32 litter depth measurements. Phenology metrics included in the correlation analysis were Time Integrated NDVI (TIN), Maximum NDVI (MAXN), and Amplitude (AMP). Values displayed in the matrix squares represent r values derived from the Pearson correlation coefficient. Correlation matrix squares with x's through them represent non-significant (*P* > 0.05) correlations.

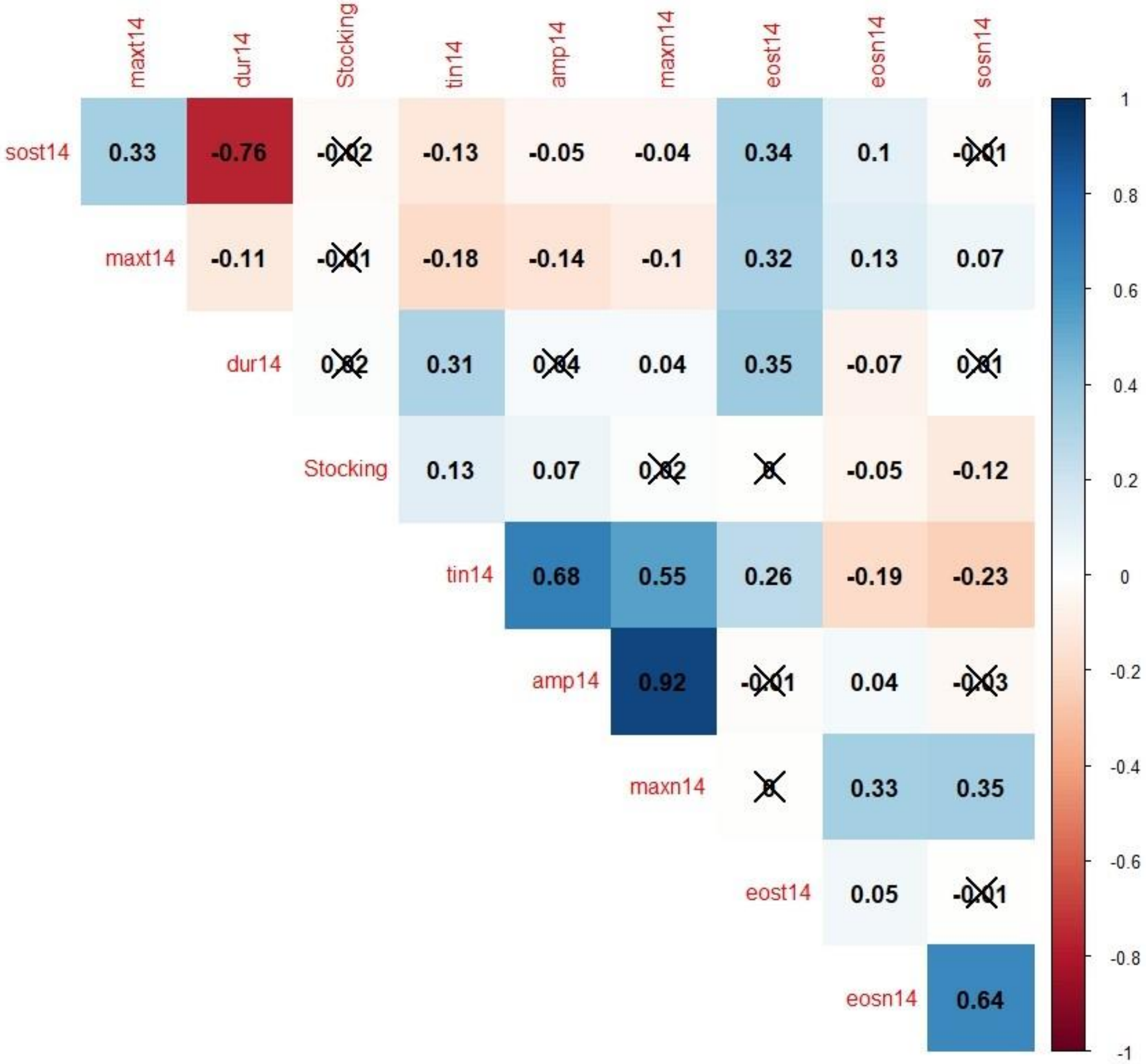


Figure 3.5: Correlation matrix between stocking density and vegetation phenology metrics in 2014 in Clark County, Kansas, USA. Grazing data was acquired from 62 pastures, with stocking density estimated as year-long cattle head per pasture acreage. Vegetation phenology metrics were calculated in 2014 by the USGS Earth Resources Observation and Science Center (EROS). Phenology metrics included in the correlation analysis were Amplitude (AMP), Duration (DUR), NDVI at the start of the growing season (SOSN), date of the start of the growing season (SOST), NDVI at the end of the growing season (EOSN), date of the end of the growing season (EOST), maximum NDVI (MAXN), date at which maximum NDVI occurs (MAXT), and time integrated NDVI (TIN). Correlation matrix squares with x's through them represent non-significant (*P* > 0.05) correlations.

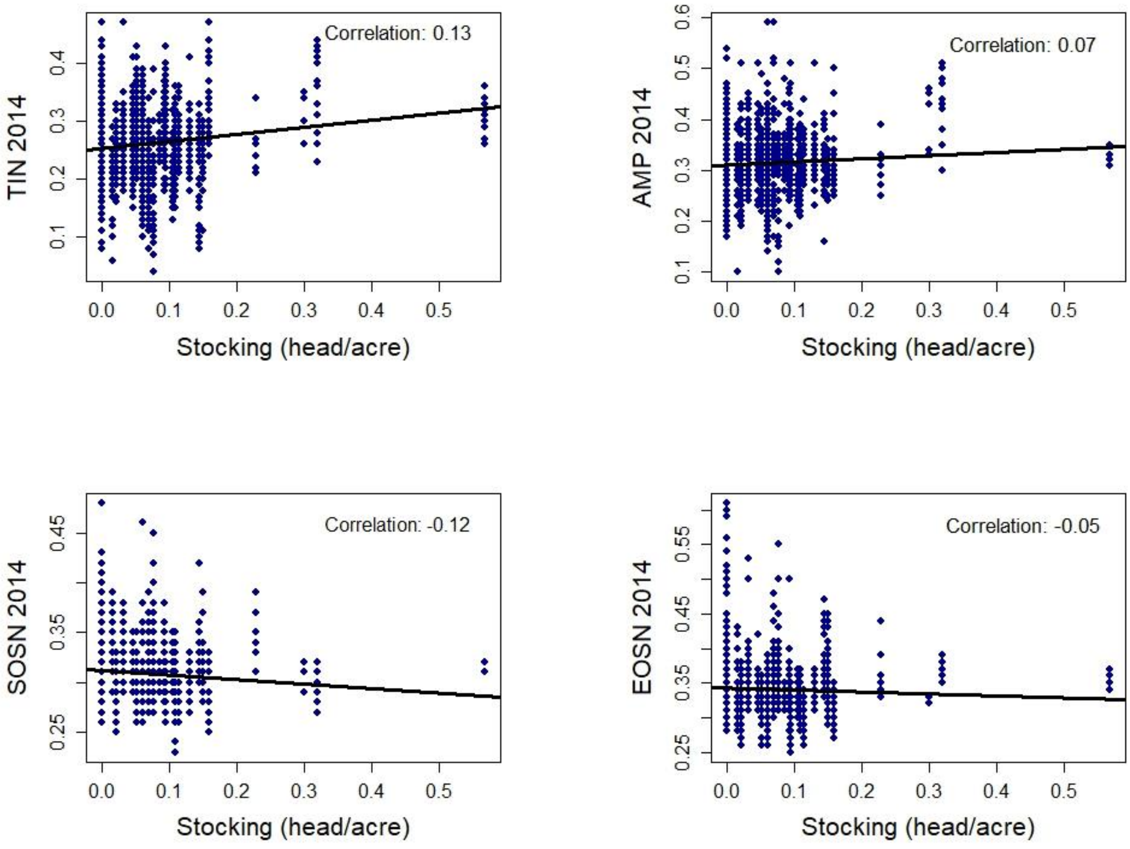
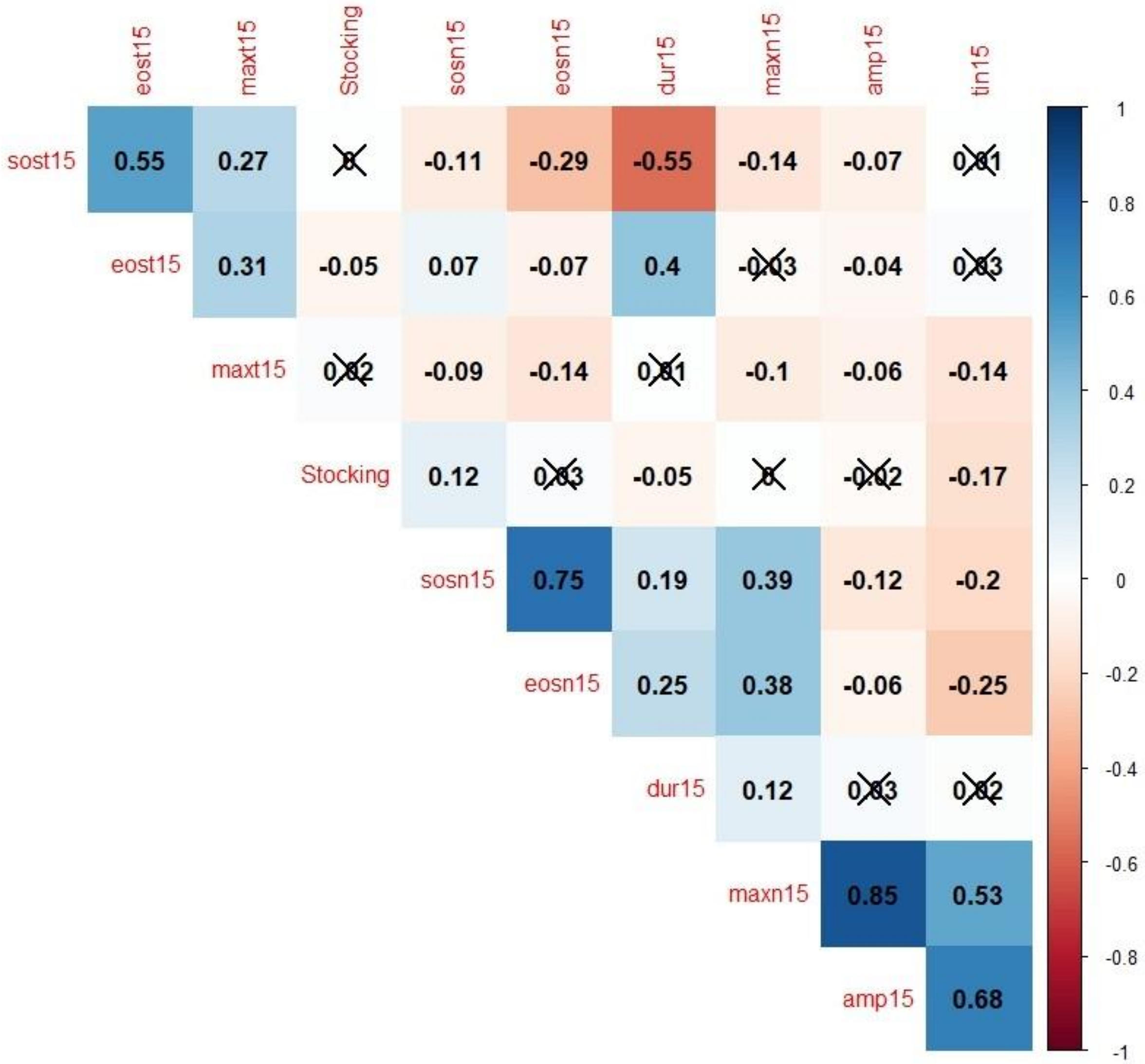


Figure 3.6: A scatterplot of TIN, AMP, SOSN, and EOSN values as a function of stocking density in Clark County, KS, USA in 2014. The black fitted line visualizes the significant negative and positive correlations between TIN, AMP, SOSN, and EOSN and stocking density. Blue circles are values of each phenology metric extracted from pixels within each of the 62 pastures included in the analyses.



	eost15	maxt15	Stocking	sosn15	eosn15	dur15	maxn15	amp15	tin15
sost15	0.55	0.27	0	-0.11	-0.29	-0.55	-0.14	-0.07	0.01
eost15		0.31	-0.05	0.07	-0.07	0.4	-0.03	-0.04	0.03
maxt15			0.02	-0.09	-0.14	0.01	-0.1	-0.06	-0.14
Stocking				0.12	0.03	-0.05	0	-0.02	-0.17
sosn15					0.75	0.19	0.39	-0.12	-0.2
eosn15						0.25	0.38	-0.06	-0.25
dur15							0.12	0.03	0.02
maxn15								0.85	0.53
amp15									0.68

Figure 3.7: Correlation matrix and associated *r* values between stocking density and vegetation phenology metrics in 2015 in Clark County, Kansas, USA. Grazing data was acquired from 62 pastures, with stocking density estimated as year-long head of cattle per pasture acreage. Vegetation phenology metrics were calculated in 2015 by the USGS Earth Resources Observation and Science Center (EROS). Phenology metrics included in the correlation analysis included Amplitude (AMP), Duration (DUR), NDVI at the start of the growing season (SOSN), date of the start of the growing season (SOST), NDVI at the end of the growing season (EOSN), date of the end of the growing season (EOST), maximum NDVI (MAXN), date at which maximum NDVI occurred (MAXT), and time integrated NDVI (TIN). Correlation matrix squares with x's through them represent non-significant (*P* > 0.05) correlations.

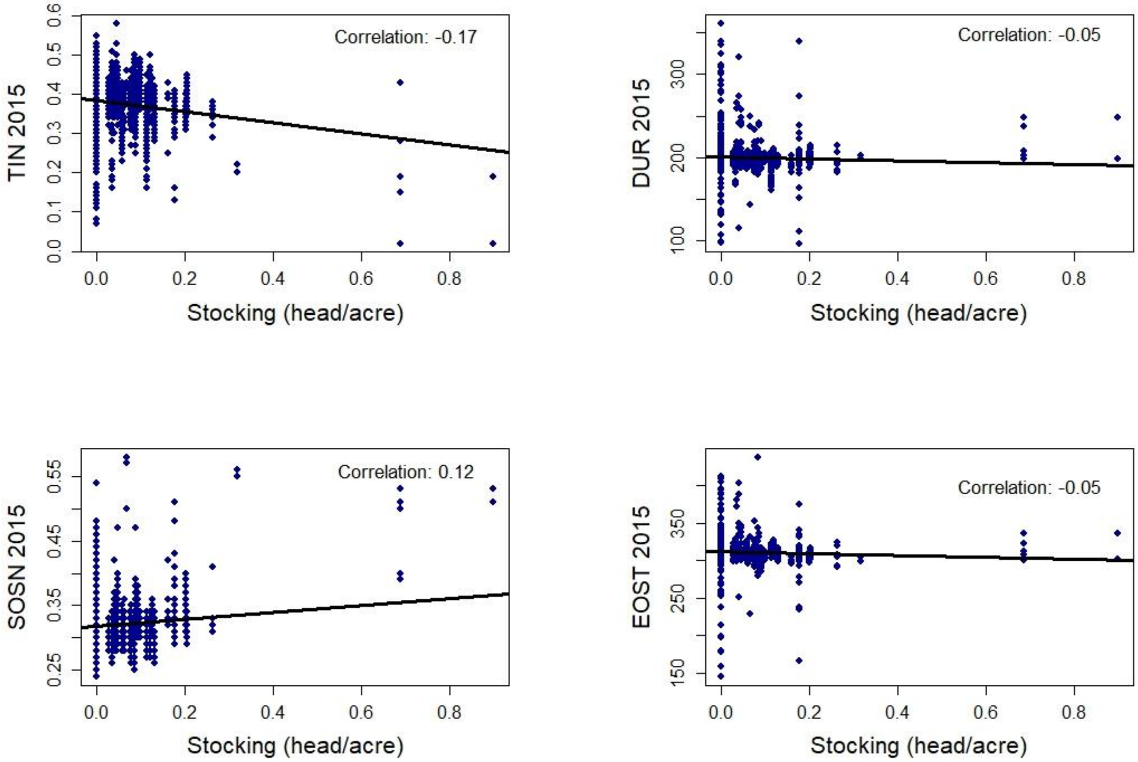


Figure 3.8: A scatterplot of TIN, DUR, SOSN, and EOST values as a function of stocking density in Clark County, KS, USA in 2015. The black fitted line visualizes the significant negative and positive correlations between TIN, DUR, SOSN, and EOST and stocking density. Blue circles are values of each phenology metric extracted from pixels within each of the 62 pastures included in the analyses.

Table 3.1: The 9 NDVI-based vegetation phenology metrics used in my correlation analyses and their descriptions. All metrics are calculated and maintained by the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center. Each phenology metric is calculated from weekly NDVI composites over a one-year period. Data is freely available from the USGS Phenology Viewer (https://phenology.cr.usgs.gov/viewer/).

Phenology Parameters	Description
SOST → Start of the growing season, time	Day of year at which a measurable photosynthetic increase takes place after senescence.
SOSN → Start of the growing season, NDVI	NDVI value of the first measurable photosynthetic increase after senescence.
EOST → End of the growing season, time	Day of year at which there is a measurable decline in photosynthetic activity.
EOSN → End of the growing season, NDVI	NDVI value on the day that there is a measurable downward trend in photosynthesis.
MAXN → Maximum NDVI	Highest level of photosynthetic activity detected in the growing season.
MAXT → Maximum NDVI, time	Day of year associated with the MAXN.
AMP → Amplitude	Difference between the SOSN and MAXN values.
DUR → Duration	Length of the growing season (i.e. the difference between the SOST and EOST).
TIN → Time Integrated NDVI	Cumulative integrated photosynthetic activity across the growing season.