APPLICATIONS OF TIME-LAPSE IMAGERY FOR MONITORING AND ILLUSTRATING ECOLOGICAL DYNAMICS IN A WATER-STRESSED SYSTEM

by

Emma M. Brinley Buckley

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APPLICATIONS OF TIME-LAPSE IMAGERY FOR MONITORING AND ILLUSTRATING ECOLOGICAL DYNAMICS IN A WATER-STRESSED SYSTEM

Emma Brinley Buckley, M.S.

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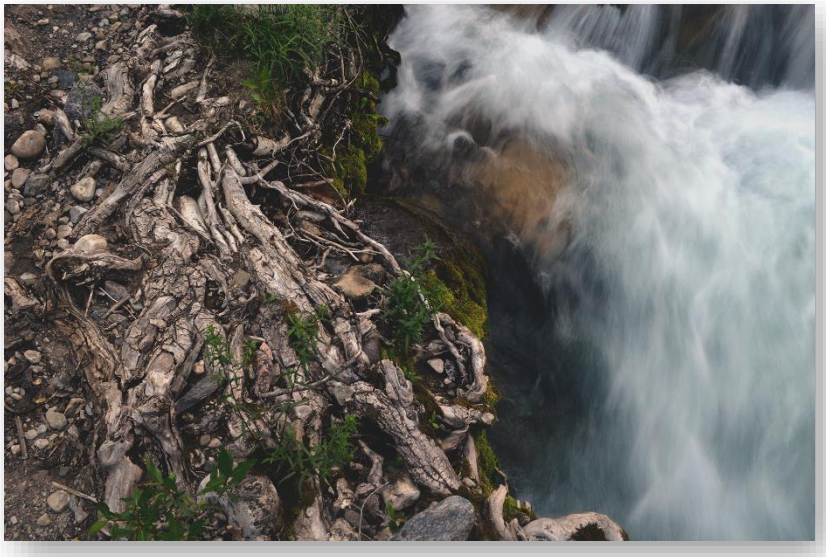
Advisor: Craig R. Allen

Understanding and perceiving the natural world is a key part of management, policy, conservation, and inevitably for our future. Increased demand on natural resources has heightened the importance of documenting ecosystem changes, and knowledge-sharing to foster awareness. The advancement of digital technologies has improved the efficiency of passive monitoring, connectivity among systems, and expanded the potential for innovative and communicative approaches. From technological progression, time-lapse imagery has emerged a valuable tool to capture and depict natural systems. I sought to enhance our understanding of a water-stressed system by analyzing imagery, in addition to integrating images with data visualization to illustrate the complexity of a river basin in central Nebraska. Image analysis was used to quantify wetland water inundation and vegetation phenology. These measurements from visible changes were combined with less visible data from additional passive monitoring to examine the relationship between vegetation phenology and bat activity, as well as wetland inundation and water quality. Moreover, time-lapse data sequences were constructed by integrating time-lapse imagery with data visualization in an interactive digital framework to examine the applications for communicating social-ecological dynamics. Findings suggest vegetation phenology was differentially associated with seasonal bat activity, possibly related to migratory versus resident life history strategies. In regards to examining wetland hydrology, water inundation was found to be correlated with nitrate, dissolved oxygen, and DEA, and

negatively correlated with water temperature, indicating the importance of understanding water levels. AEM-RDA analysis identified several significant temporal patterns occurring with the wetland as well as the river site. Similarities between river and wetland patterns were suggestive of regional conditions driving fluctuations, while discrepancies were indicative of structural, biological, and local differences within individual sites. In examining communicative applications, time-lapse data sequences depicted a range of ecological dynamics while linking visible and invisible occurrences. The framework shows potential to offer a tangible context with explanatory content to aid in understanding environmental changes that are often too subtle to see or beyond the temporal scale of unaided human observation. Overall, cumulative findings suggest time-lapse imagery is of dual utility and has high potential for collecting data and illustrating ecological dynamics.

TO THOSE WHOSE WANDERING PATHS HAVE GUIDED MINE.



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CHAPTER 1. INTRODUCTION AND OVERVIEW

"To the student of ecology, the camera is not a toy."
-Frederic E. Clements, Research Methods in Ecology, 1905

Understanding and societal perception of the natural world is a guiding factor for management, policy, and inevitably our future. Ecosystems are inherently complex and variable, but exhibit familiar occurrences, predictable cycles, and characteristic patterns across scales of time and space. However, some cycles, patterns, or trends may occur at scales challenging for humans to observe, actively monitor, or comprehend. During a time of unprecedented global change, documentation of ecosystem changes are essential to measure and understand biotic and abiotic responses (Visser & Both 2005). Moreover, novel approaches of knowledge-sharing are necessary to engage audiences and foster understanding of social-ecological dynamics. Time-lapse imagery offers multifunctional applications to capture change over time and visualize social-ecological dynamics.

Almost all natural systems have been significantly altered, diminished, or degraded by human-use activities, which in turn, have affected ecosystem processes, cycles, and beneficial ecosystem services. The Central Platte River Basin in Nebraska, one of the most significant river systems in the Great Plains (Williams 1978), demonstrates the complexity and importance of a human-dominated and highly modified system. An internationally important resource for wildlife (Aiken 1998), the approximately 80 mile stretch of Platte River, from Overton to Chapman, Nebraska, is a hemispheric bottleneck in the central flyway, a migratory corridor for millions of migrating birds. This critical section of river basin also provides habitat for endangered and threatened species such as the Interior Least Tern *(Sterna antillarum*

athalassos), Piping Plover *(Charadrius melodus),* Whooping Crane *(Grus americana)*, Pallid Sturgeon (*Scaphirhynchus albus*)*,* and Northern Long-eared bat *(Myotis septentrionalis*). The ecological importance of the Platte River is mirrored by the economically significant allocation of water to sustain municipalities, industries, hydroelectric-power, and agricultural irrigation.

Historically, the hydrograph of the Platte River Basin was dominated by climatic events and seasonal pulses, with peak flows driven by snowmelt in the spring (Snow & Spalding 1988). The physical, hydrological, and biological structure of river ecosystems is shaped by the timing and duration of streamflow (Poff et al. 1997). Infrastructure to generate electricity and to supply water for human- use activities has removed or retimed 70% of the Platte River's natural flow regime (Brei 2005, Williams 1978), which has significant implications on ecological functioning (Cooper 1993, Poff et al. 1997). Reduced streamflow and land-use changes have altered stream reach characteristics, decreased wildlife habitat, and redefined the dynamics and environment of the central Platte River Basin (Swanson 1998, Eschner 1981, Johnson 1994).

The significance of the Platte, and the competing and conflicting water uses have prompted research and management efforts focused on the Central Platte River Basin. Various federal, state, and non-profit organizations have implemented conservation and management efforts in the area, often prompted by lawsuits (Aiken 1998, National Research Council 2004). Some of the prominent entities include the Platte River Recovery Implementation Program, Nature Conservancy, The Audubon Society, the Crane Trust, Nebraska Game & Parks, U.S. Geological Survey, and the US Fish & Wildlife Service. A novel undertaking, the Platte Basin Timelapse Project (PBT; www.plattebasintimelapse.org) was founded in 2011 as a multimedia project to inspire, build community, educate, and create digital stories in regards to the

watershed. The foundational medium of PBT is more than 40 time-lapse cameras stationed throughout the basin. Each camera is deployed year round and captures one photo every daylight hour; the result is a vast archive of over 500,000 images documenting hydrological, morphological, and phenological changes for more than 900 river miles in three states. Time-lapse imagery captured in the central Platte River Basin of Nebraska is a central component of this thesis.

Review of Time-lapse Imagery in Natural Systems Research and Communication

Time-lapse imagery occupies an important niche in ecology as a tool for monitoring, observing and documenting change at multiple temporal scales and frequencies. Sometimes called repeat photography, or rephotography, the techniques are of the same concept and often used synonymously, but can vary according to the researcher and subject of study (Sonnentag et al. 2012). Repeat photography often requires examining a historic photograph, revisiting the site, or photo-point, a quantity of time later (months, years, decades), and recreating an identical frame or photo-pair of the same scene (Butler & DeChano 2001, Khan et al. 2013), essentially matching a new photograph to a historic image (Rogers et al., 1984). Time-lapse is typically applied as a higher temporal frame-rate frequency; less time in between sampling intervals (minutes, hours, days), usually with equipment remaining in place, but can span for an extended temporal duration (i.e.: a photograph a day for three years) (Parajka et al. 2012, Kramer & Wohl 2014,). Many studies use the phrase repeat photography synonymously with the concept of time-lapse photography (Andrews et al. 2011, Migliavacca et al. 2011). This thesis recognizes repeat photography and rephotography as a fundamental basis of time-lapse photography with slight systematic differences in historical framework but contextually interchangeable.

The method of repeat photography in the natural sciences has existed since the late 1800's. Glaciologists, such as Sebastian Finsterwalder in 1889, began using the technique in the Alps, Rocky Mountains, Sierra Nevada's, and Alaska to survey and document glaciers (Gilbert 1904, Hattersley-Smith 1966, Webb 2010). The early 1900's lead to the use of repeat photography in geologic monitoring such as erosion in bedrock (Bryan & La Rue 1927) and changes in range-land (Lockett 1939).Repeat photography became a more popular tool after the 1940's and focus shifted to land-use and vegetation changes (Pope 1957, Shantz & Turner 1958). One of the largest collections of archived repeat photographs, The Desert Laboratory Repeat Photography Collection hosted by the U.S. Geological Survey, began, in the 1960's, to document vegetation change in the southwest United States. Historical images from the 1800's were rephotographed and it has since been the foundation of numerous landscape studies (Hastings and Turner 1965; Villerreal 2011; Webb & Leake 2006, Cohn 2003). An extensive historical review of repeat photography has been outlined in two books, Bibliography of Repeat Photography for Evaluating Landscape Change (Rogers et al. 1984) and Repeat Photography: Methods and Applications in the Natural Sciences (Webb 2010).

Advances in digital technology have improved the efficacy, cost, and benefits of time-lapse photography, making the method an easier, more efficient, and readily available tool. Image analysis utilizing image processing software such as ESRI, Photoshop, VegFrac, and ImageJ, has provided the ability to extract detailed data and numerical information from color channels, pixels, and measurements. The development of indices using algorithms to document ecological change based on empirical data have evolved digital time-lapse cameras to in-situ sensors.

Utilized for passive monitoring, time-lapse imagery is capable of documenting ecological trend, condition (Hart & Laycock, 1996), and providing quantitative data to assess landscape processes (Bradley et al., 2010). As a ground-based instrument, time-lapse imagery has been used to assess glacier fluctuations (Byers 2007), long-term trends in mountain systems (Skovlin 1995, Johnson 2003), forest vegetation (Zier & Baker 2006), environmental controls on vegetation (Forkel et al. 2014), the association of carbon flux and vegetation (Migliavacca et al. 2011), and phenology (Richardson et al. 2009, Sonnentag et al. 2012). In addition, Frankl et al. (2011) examined channel dynamics and the hydrological regime of a river system using time-lapse imagery. Aside from technological advances increasing the availability of camera systems, time-lapse imagery is increasingly utilized, as it is time efficient, affordable, offers detailed imagery of landscape specific sites, and compared to other methods can have better resolution and can be more relatable to the public (Roush et al., 2007, Ide & Oguma, 2010). The technology allows flexibility and control over sampling intervals and the capability to compress time to analyze ecosystem changes.

The flexibility and control provided by time-lapse imagery offers a tool to acquire data at a range of time and space which complements other data acquisition methods such as in-person observations and satellite remote sensing. In-person field observations are beneficial for detailed information requiring hands on manipulation to gather information but have numerous limitations such as logistics, lack of consistency, continuity and objectivity. (Sonnentag et al., 2012). Remote-sensing via aerial or satellite imagery offers geo referencing, a wide EMR spectrum, multiple sensors, easier spatial measurements, and a larger field of view. However, there is limitations to the temporal and spatial resolutions, it’s challenging to recapture an exact

field of view (flying an aircraft every hour and waiting for a satellite to hit a specific position), and it can be financially demanding (Kull 2005). Time-lapse imagery augments data acquisition by fulfilling a gap between large-scale (satellite) and small-scale (in-person observations) methods to benefit research initiatives by collecting data on a more contiguous scale and improving the ability to scale-up datasets.

Studying the mechanisms influencing ecological variability is a difficult feat, but communicating this complex concept to the general public may be even more challenging. Time-lapse photography has emerged as a prevalent technique used in mainstream media and film. It can powerfully visualize natural occurrences which are often difficult to observe at real time, in a cinematic production, documentary, or new media framework to engage audiences that academia may not reach. Moreover, the temporal framework of time-lapse imagery provides optical excitement and captivation while simultaneously illustrating changes and complex dynamics in systematic motion over time.

Although time-lapse imagery has been utilized to capture natural phenomena since the early 1900's, the advancement of technology has drastically altered its application, appealing to cinematographers, the public, and science-journalists alike. One of the original users of time-lapse photography to capture the changes in the natural sciences was Dr. John Ott. In the 1930's Dr.Ott experimented with self-built time-lapse equipment to photograph plants in various lighting in his greenhouse. His experimental approaches were featured on TV shows and movies including Walt Disney's 1959 documentary 'Secrets of Life' (Anaclerio 2002). Following Ott's legacy, Godfery Reggio's 1989 'Qatsi' trilogy is an abstract series of three documentaries that generated a cult following. The series utilizes repeat photography to visually explore the

relationship between people, nature, and technology (Dempsey 1989). Recent use of time-lapse imagery in film include Disneynatures'© movie 'Wings of Life' (Candler et al. 2011) and BBC©'s 'Planet Earth' (Fothergill et al. 2007).

In the context of climate change and ecosystem communication, 'Chasing Ice' and the Extreme Ice Survey (Chasing Ice 2012) was a catalyst for repeat photography. Nature photographer James Balog installed over 20 time-lapse cameras in the Artic to document retreating glaciers. The captivating and expressive footage was turned into a documentary that reached diverse audiences through screenings in 172 countries, 75 film festivals, students at 70 universities, and policy makers in the White House, US Congress, and United Nations (Chasing Ice 2012).

Time-lapse photography offers a multifunctional technique to extract quantitative and qualitative data for scientific inquiry, as well as convey ecological dynamics. It can illustrate changes that may be difficult to observe with the human eye, such as processes functioning at slower time-scales or occurrences that are challenging or too elusive to observe. The wide array of data acquisition and communication applications highlight the value of this technology to understand natural systems. This thesis explores the application of time-lapse imagery to document and communicate changing dynamics in an ecological and economically important watershed.

Thesis Overview

This research demonstrates the applications of time-lapse imagery as a tool to capture ecological fluctuations and as a communicative method to visualize complex system dynamics of a stressed watershed in the Great Plains of central Nebraska. Specifically, I utilize time-lapse

cameras as ground-based sensors for passive monitoring to document changes in surface water and vegetation phenology in 2013, 2014, and the spring of 2015. To communicate the dynamics of complex systems, I explore the integration of time-lapse images and data visualization in a digital new media format. Chapter 2 explores the integration of time-lapse imagery and data visualization, into time-lapse data sequences, within an interactive new media framework to convey and visually examine visible and often invisible ecological dynamics. Chapter 3 examines water quality and identifies temporal fluctuations using multivariate time-series modeling. Chapter 4 examines relative bat activity in relation to vegetation phenophase and additional ecological variables. Chapter 5 assesses landscape vegetation phenology acquired from time-lapse imagery and the relationship to satellite derived measurements. Overall, the objective of this thesis is to illustrate a range of scientific and communication applications using time-lapse imagery, with the intent to enhance understanding of natural systems and social-ecological dynamics.

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CHAPTER 2. THE DUALITY OF TIME-LAPSE IMAGERY TO CAPTURE AND CONVEY NATURAL SYSTEMS

Introduction

Significant ecological change has heightened the need to monitor natural systems and progress societal understanding of connected social-ecological systems. Increased demand on natural systems to provide vital resources for society has resulted in significant ecological change and, consequently, challenged the earth's capacity to sustain human life (Folke et al. 2011, Millennium Ecosystem Assessment 2005, Chapin et al. 2010). To effectively manage our natural systems, innovative methods to monitor and examine ecological changes, as well as to communicate and share knowledge about natural systems are needed. The complementary attributes of aesthetic appeal and observational documentation provided by digital time-lapse imagery offers a dynamic approach to enhance understanding of natural systems and the role of humans in ecological change. We examine dual utilizations of time-lapse imagery; as a tool for passive monitoring and as a method for communicating ecological change through an interactive new media platform integrating imagery and data visualization. This duality synthesizes art and science to capture and illustrate a stressed watershed in the Great Plains of the United States.

Human activities have significantly altered natural systems, increasing the vulnerability of ecosystems to perturbations, increasing stress on natural systems, and affecting social-ecological dynamics. To manage our natural resources and mitigate potential threats, monitoring and documentation is necessary to detect biotic and abiotic changes and measure the response of natural systems to anthropogenic impacts. Because knowledge-sharing is a key process for building adaptive capacity and resilience in social-ecological systems (Chapin et al. 2010),

public communication is equally as necessary for management, mitigation, and to foster sustainability. Societal understanding of the natural world and the role of humans in it is necessary to make informed decisions regarding policy (Berkowitz et al. 2005) and is essential to build support for science and to foster change (Jordan et al. 2009).

The advancement of digital technology has contributed to an increase in data acquisition and observational efficiency, information exchange, and high connectivity among social-ecological systems, which has redefined how individuals interact with and infer meaning about the natural world (Sagarin & Pauchard 2010, Boehnert 2012). Digital time-lapse imagery has emerged from technological progress as a dually advantageous method for documenting and conveying ecological systems. Ecology and photography are historically and innately founded in observation (Sagarin and Pauchard 2010). This fundamental basis has enabled a symbiotic affiliation; photographers have capitalized on capturing the beauty of the natural world, and simultaneously, images have proven to be a valuable tool and powerful voice for the natural world (i.e. Ansel Adams, Carleton Watkins, and William Henry Jackson). Moreover, photography has helped progress our knowledge-base of the natural world, humanity, and has played a significant role in defining various architypes that construct our understanding of social-ecological paradigms such as capitalism, conservation, and scientific inquiry (Kinsey 1992, Trachtenberg 1989, Truettner 1991, Hales 1988, DeLuca & Demo 2000). Digital advancements in camera technology have improved the capabilities to more efficiently capture, characterize, and illustrate natural system changes (Sonnentag et al. 2012, Bradley 2010).

Compared to still imagery, time-lapse imagery offers an augmented dimension with a dynamic advantage, temporal structure. A single frame or point-of-view is captured repeatedly

over distinct, controllable, iterations of time. Sequential alignment of individual frames compresses human-experienced time into a more tangible and perceptible timeframe (i.e. days to years illustrated within seconds to minutes). The compressed temporal format is capable of revealing changes that may be too subtle for the human eye to see, or slow, long-term processes that are difficult to understand, and can expose abstract patterns, relationships, and dynamics at scales otherwise difficult to resolve. Although pervasively dynamic, images are limited in their proficiency at communicating empirical data (Solomon 1992). Thus, the synthesis of data visualization and imagery can offer a communicative duality to coalesce the quantitative aspects of data and the interpretable aesthetics of imagery to convey complex social-ecological dynamics.

Many of the environmental challenges facing society are not entirely visible which contributes to societal misunderstanding or unfamiliarity (Hansen & Machin 2013). Coupling time-lapse imagery and data visualizations into time-lapse data sequences illustrates visible changes and context alongside elusive or invisible changes and content. Unaccompanied, numerical values are intangible and dull, and therefore, are restrictive in the insight they can provide regarding ecological processes, particularly when communicating with the general public. However, data visualization, the translation of numbers into aesthetic form, can assist in examining and comprehending abstract values. Reinforcing graphical representations with visually telling imagery, time-lapse data sequences offer potential to reveal latent changes, depict a more holistic conceptualization of ecological dynamics, and elucidate informative yet beautiful patterns, processes, and relationships (Gray et al. 2012).

The objective of this study was to explore the monitoring and communication potential of digital time-lapse imagery to enhance the understanding of natural systems and social-ecological dynamics. We collaborated with the Platte Basin Timelapse Project (PBT) to utilize an immense dataset of imagery. PBT is a multimedia endeavor utilizing dozens of high resolution digital time-lapse camera systems across a river basin to capture a watershed in motion. The project looks to foster awareness and build community in a water-limited landscape and has collected over half a million images as of 2016, presenting an opportunity to assess various ecological applications. An innovative integration of time-lapse imagery from the PBT archive and data visualization from passive monitoring were used to develop time-lapse data sequences to illustrate a socially and ecologically significant river system in the Great Plains.

Initial development and post-construction assessment were directed by a set of focal questions;

1. Are the time-lapse images and graphics aligned? What are the synchronicities? What information is presented in one form and not the other?
2. Are the visible/invisible dynamics, processes, and occurrences observed in the visual representations related in time? If so, what is the association and at what timescale is it occurring?
3. What narrative do time-lapse data sequences inform? Is there a place-based significance (i.e. local, global)? Are there multiple meanings that can be constructed?
4. How can time-lapse data sequences be utilized and by whom? What are the prominent benefits?

Methods

Study Site

The Platte River Basin is an economically important and internationally critical ecosystem, and a key example of a stressed and human-dominated watershed (National Resource Council 2004). As one of the most significant riverine systems in the Great Plains (Williams 1978), the Platte River in Nebraska and its tributaries, the South Platte in Colorado and North Platte in Wyoming (Figure 1), provide numerous beneficial uses such as hydroelectric power, irrigation, and recreational opportunities. In addition, the central Platte River Basin is ecologically critical and provides breeding habitat for birds, a key migratory corridor for thousands of Sandhill cranes and waterfowl, and an essential region for numerous endangered species including whooping cranes (*Grus Americana*), interior least terns (*Sterna antillarum*), and piping plovers (*Charadrius melodus*). However, the river has been redefined by extensive engineering and development, altering the hydrological, biological, and physical characteristics (Eschner 1981, Strange 1999). Historically, the hydrograph of the Platte River Basin was dominated by climatic events and seasonal pulses, with peak flows driven by snowmelt in the spring (Snow & Spalding 1988). Water-provisioning infrastructure, such as dams and diversions, engineered for industrial, agricultural, and domestic-use has removed or retimed 70% of the Platte's natural flow regime, directly and indirectly altering the structural, biological, and ecological characteristics of the watershed (Williams 1978, Aiken 1999). Reduced flood-pulses and stream flow has limited the natural structuring process of sediment-scouring and encouraged the encroachment of vegetation, resulting in deeper and narrower channels. Contrastingly, the historic morphology of the Platte was characterized by mile-wide and inch-deep braided river channels (Eschner 1981, Johnson 1994, Swanson et al. 1998). The recent modified flow regimes

have prompted legal litigation and recovery plans to manage land and restore adequate stream flows, resulting in contention among various public, industry, and governmental entities.

The study region is an approximately 90 mile section of the central Platte River Basin extending from Lexington, Nebraska, USA, eastward to Grand Island, in south central Nebraska. Data was collected from three research sites within the central Platte River Basin; Plum Creek Complex (PCC), Rowe Sanctuary (RS), and Derr Wetland (DW) (Figure 2). PCC (40.679, -99.401667) near the town of Overton, Nebraska, is the furthest west location, situated on the south channel of the Platte River. The area is managed for endangered avian habitat and thus, the landscape is disked to maintain minimal vegetation. The surrounding land is historic cropland that has been reseeded back to native grass and the remaining land is hay meadow. RS study site (40.6675, -98.8924), near Gibbon, Nebraska, is maintained by the National Audubon Society and adjacent to the Platte River's south channel. The site is characterized by riparian wetlands, forested patches, and agricultural fields. The third research location, DW (40.74102, -98.57278), near Wood River, Nebraska, is a section of the Platte River Prairies tract of land owned and managed by The Nature Conservancy. In 2011, a wetland slough situated on the tract of native prairie was restored from a sand and gravel mining pit. Adjacent to the tract is a patch of mixed riparian forest and privately owned agricultural fields.

Time-lapse Camera Systems

High resolution digital camera stations were installed at each research location; RS, PCC, and DW (Figure 3) by the Platte Basin Timelapse project. Each camera station is comprised of a Nikon D300 DSLR camera with a 12.3 megapixel crop sensor (DX) and Nikkor 18-70mm 1:3.5-

4.5 lens. A TRLcam intervalometer (TRLcam.com) controls the interval settings and the timing is adjusted by a GPS module to account for differing daily sunrise and sunset times. The intervelometer was generally set to capture one red-green-blue (RGB) color channel image every hour beginning at sunrise and ending at sunset, although occasionally was set to capture specific phenomena at other intervals (i.e. 15 minutes). The equipment is contained within weatherproof housing constructed from ultra-violet stabilized polycarbonate plastic made by Serpac with modifications of optical glass, aluminum lens hood, and ball mount to secure the camera to a mounting pole approximately 2.5 meters above ground. The systems are powered by a 30 watt solar panel and stored in a lithium ion battery. Camera operation is verified daily by cellular technology that sends an image via email to confirm acquisition. The images are automatically uploaded to PBT's 1.5 terra-byte image library and accessible through Phocalstream, software technology developed by the Jeffrey S. Raikes School for Computer Science and Management at the University of Nebraska – Lincoln.

Proximal sensing: Vegetation Dynamics & Water Inundation

Ground-based or proximal sensing is an increasingly applied technique in ecological research for monitoring systems, assessing biotic and abiotic change, and evaluating management decisions (Crimmins & Crimmins 2008, Richardson et al. 2009). We utilized time-lapse cameras to quantitatively assess the temporal characteristics of vegetation at all sites and water inundation at one site, DRW. At each location, three images a day were selected between the hours of 10:00 and 14:00 for standardization of sun position and shadow. The selected images were then vetted for variations within the frame of view and those with discrepancies

were discarded (weather, spider web, etc.). If possible, additional images without interferences were selected to complete the sequence of three images a day per site.

Vegetation is a deterministic factor in the functioning of natural systems (Toomey 2015, Wiegand 2008). Phenological changes in vegetation, such as the timing of budburst, green-up, flowering, and senescence, are indicative of energy availability throughout trophic cascades (Pettorelli et al. 2011), alterations in seasonal patterns and inter-annual climatic changes (Dunn & Beurs 2011), and a key component in understanding ecological responses to a globally changing climate (Schwartz et al. 2006, Xiao and Moody 2004). To assess vegetation phenology, particularly green-up and senescence, imagery was batch analyzed by selecting a region of interest (ROI) within each image. The ROI was a standardized selection at each site that encompassed predominately vegetation. The average digital number for each Red-Green-Blue (RGB) color channel within the ROI was used to calculate the Green Chromatic Coordinate vegetation index (Gcc, Equation 1). Gcc is robust to variations in weather and light illumination (Sonnentag 2012), and has been widely used to characterize phenophase and variations in vegetation (Richardson et al. 2009, Zhao et al. 2012).

$G_{CC}= DN_G/ DN_R+DN_G+DN_B$ (Equation 1; Wyszecki and Stiles 1982, Gillespie et al. 1987)

In addition to vegetation phenology, imagery captured at DRW was assessed for hydrological changes by quantifying water inundation through image analysis. The hydrologic regime of DRW, although influenced by the hydrology of the Platte River, is driven by a ground-water fed stream and has varying differences in system characteristics and water contributions

compared to RS and PCC, such as surface water runoff, precipitation, evapotranspiration, vegetation, and surface area. Furthermore, DRW does not have a stream gauge and thus, changes in hydrology were previously not measured. Therefore, we surmised time-lapse imagery may provide an efficient and necessary technique to monitor the amount of surface water over time at the wetland. Images were batch analyzed in Image J (Schneider 2012, Image J software, NIH, Bethesda, Md., U.S.A.), an image analysis program created by the National Institute of Health, using a custom script modified from a health sciences microscopy technique (Hadi et al. 2011, Schneider et al. 2012, Hakonen et al. 2014). RGB images were transformed to the cylindrical hue-saturation-value (HSV, also called HSB; brightness) color space for more accurate color statistics (Chang et al. 2010). Hue is the spectral property of a specific color, saturation is the intensity perception of a color, and value denotes the perception of brightness of a color. The hue slice of the HSV stack was cropped to a region of interest (ROI) which encompassed the most wetland area and discarded the terrestrial landscape to reduce errors associated with variations between images (Figure 3). The ROI was converted to a binary (black and white) image where pixel values were 1 or 0. The level of thresholding was determined by an automatic function that divided the image into background (0) and objects (1) by producing a test threshold and calculating the average of pixels above and below the test threshold. Area statistics were calculated using the function ‘Measure’, which was selected for area fraction with an overlaying mask. The results were output to a CSV file organized by file-name and date. An accuracy check was completed using visual comparison between the original image and the produced mask and measurements deemed inaccurate were discarded. Batch analysis results of approximately three

values per day were averaged to a daily mean of water inundation, or, a numerical value representing the percentage of pixels in the ROI classified as water.

Climatic/Environmental Variables

Stream gauge data was available for RS and PCC, and thus, streamflow measurements were obtained for the river channel study sites from corresponding United States Geologic Survey (USGS) streamflow-gaging stations; RS from station ID 06770200 near Kearney, Nebraska (Latitude 40°41'08", Longitude 99°26'20" NAD27) and PCC from Site ID 06768025 near Overton, Nebraska (Latitude 40°40'44", Longitude 99°29'21" NAD83).

Time-lapse Data Sequences

To visualize system changes over time, time-lapse imagery was coupled with data visualizations to construct time-lapse data sequences. We explored multiple techniques and software to accommodate various platforms, media, and frameworks. Static examples were developed for avenues with one-dimensional platforms or constrained format requirements, such as posters, paper publications, and thesis repositories. Static constructions also acted as an architectural frame and a stepping point for designing interactive examples. Graphics were created using R statistical analysis software, and the Adobe Creative Suite, including Illustrator and Photoshop. In Adobe After Effects, videography and time-lapse video were constructed and rendered with a duration of five seconds per image and an overlapping dissolve of two seconds. The time and location of time-series data points were matched with the time-stamp and site of

corresponding imagery. Digitally interactive illustrations were constructed using HTML, CSS, and JavaScript with D3 as the primary library.

Results

Proximal Sensing

In a water-stressed system within the Great Plains of Nebraska, we examined dual applications of time-lapse imagery to monitor and communicate ecological dynamics. Employed as proximal sensors, time-lapse cameras documented visible changes within a riverine system and image analysis of the RGB color channels provided quantitative and qualitative time-series data. Modelling Gcc over time revealed distinct trends and seasonal characteristics of vegetation phenology within the riparian zone of the river and wetland (Figure 5). However, there were observed differences between sites and years. For example, in 2013 the initial green-up phenophase began later at PCC and DRW compared to 2014 and 2015. Contrastingly, all years were relatively similar at RRC. Changes in vegetation from management activity were also evident from the data. In 2014 a decline in greenness, followed by an immediate increase, was observed in Gcc graphed over time, an effect of haying/cutting associated with land management and reflected by the vegetation index.

Metrics of water inundation at DRW were evaluated by comparing the original imagery to the produced masks. Overall, the results were accurate, but a discrepancy among years was observed. In 2013, a total of 308 images were batch analyzed for water inundation. Of these, 69 of the corresponding masks were deemed inaccurate and discarded for an error rate of 0.22. In 2014, 635 images were analyzed and 61 were discarded for an error rate of 0.09. In 2015, a total

of 281 images were analyzed and of those, two were discarded, resulting in a <0.01 error rate. Visual comparison between the hydrographs at RRC and PCC and water inundation at DRW exhibited general similarities of temporal fluctuations and patterns throughout seasons and in regards to weather events. A slight delay was observed at DRW compared to the river channel sites; a reasonable observation given the more extensive system of streamflow for water to reach the wetland (Figure 6).

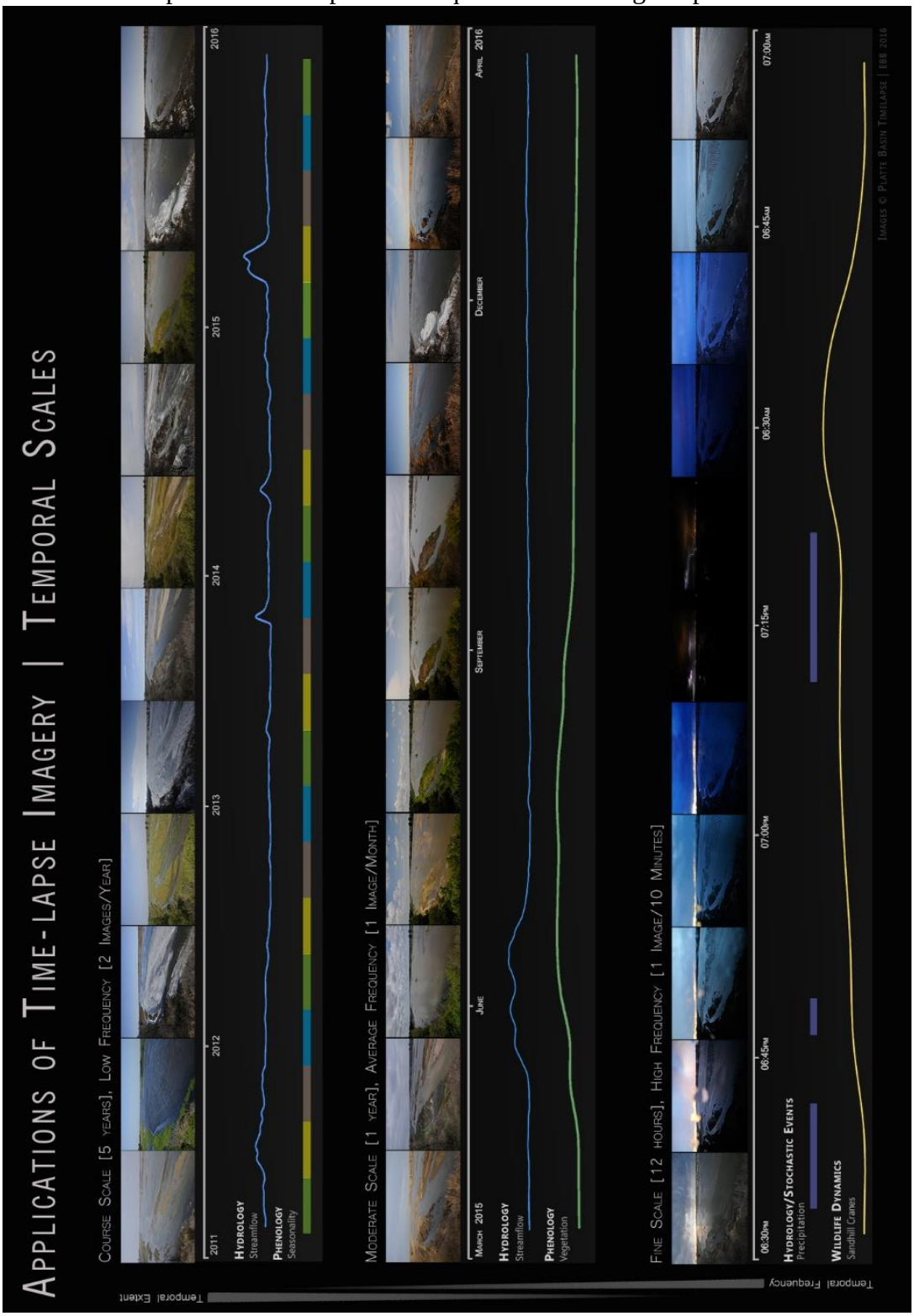
We surmised that the flexible nature of time-lapse imagery in a digital environment may be better apt to convey the nonlinearity, transitions, and shifting states inherent of complex systems. This integration elucidated a range of visible, subtle, and invisible changes, ecological phenomena, and evidence of an altered system; the scale at which pattern and process take place, vegetation dynamics including the encroachment of woody and invasive vegetation, river hydrogeochemistry, and a scheduled and controlled streamflow due to dam releases. The following examples demonstrate multifaceted applications and framing of time-lapse imagery to convey and explore natural systems and validated our conjecture.

Digitally interactive examples are available at the following URLs:

- http://www.ebrinbuck.com/ATZ.html
- http://www.ebrinbuck.com/OXY.html
- http://www.ebrinbuck.com/hydropower.html

Applications of Time-lapse Imagery

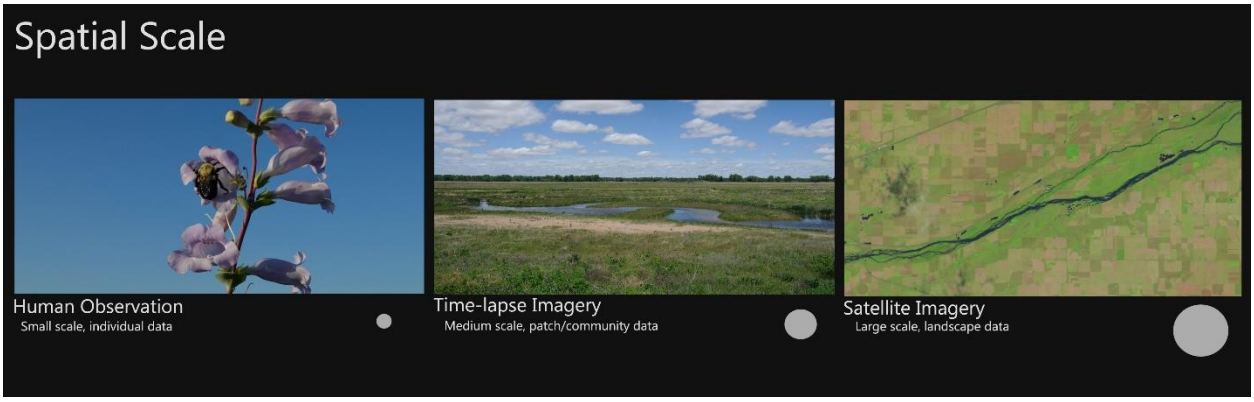
Figure 7: Static example of a time-lapse data sequence illustrating temporal scales.



Time-lapse imagery augments the ability to capture change at multiple temporal scales to observe and monitor natural systems, as well as communicate ecological patterns and processes. Peterson and Parker explain, “When we observe the natural world, the things we discerns, patterns of those things, and the relationships among these things, are determined by the scale at which we observe- the scale of observation, both grain and extent.” (Peterson & Parker 1998). Time-lapse camera stations could be adjusted manually to vary time intervals, thereby capturing the river system at high, moderate, and low scales of time (Figure 7). The difference in ecological elements discerned at each scale of observation offers insight into the importance and value of documentation across a range of scales and the capabilities presented through the applications of time-lapse imagery. The temporal structure, versatility, and range of temporal scale provided by time-lapse imagery displays ecological rhythms, variability, and stochastic events. Broadly, ecological rhythms are environmental processes or biological occurrences with defined periodicity such as phenology, diel cycles, and life history strategies. At a large temporal scale, time-lapse imagery is able to capture ecological rhythms and interannual fluctuations, depicted as changes in hydrology, geomorphology, and seasonality (Figure 7, ‘Coarse Scale’). Image acquisition a high temporal extent and a low grain is valuable for assessing systems over time, restoration initiatives, and landscape impacts of climate change. At a moderate temporal extent and grain, time-lapse imagery captures variations within seasons, fluctuations in streamflow, and the influence of environmental factors such as weather. Documentation at a moderate temporal resolution are applicable for evaluating the response of biotic and abiotic elements to weather, such as variations in hydrology and water quality, the rate of vegetation phenophase, and processes within a season (Figure 7, ‘Moderate Scale’). At a fine scale,

comprised of high temporal frequency and short temporal extent, imagery is valuable for capturing rapid processes, in-depth details, or documenting occurrences that may be too sensitive to observe extensively in person, such as the roosting patterns of Sandhill cranes (*Grus Canadensis*) (Figure 7, 'Fine Scale'). The temporal versatility of time-lapse exemplified by a range of scales makes it a valuable tool for research, but moreover is a valuable mechanism to communicate relationships and processes that can be challenging to understand when observation is temporally limited or at one temporal scale.

Figure 8. Representation of the spatial scales of observation. First image depicts data acquisition via in-person observations. The second image illustrates the spatial scale of digital time-lapse imagery to observe changes at a moderate-extent in the landscape and bridge the spatial divide. The third image is of satellite imagery capturing a global view. All imagery is of Derr Restoration Wetland (DRW) in the central Platte River Basin of Nebraska in 2014.



In combination with the range of temporal scales, the spatial scale of time-lapse imagery is valuable for understanding natural systems, especially climate change research and the response of biotic and abiotic factors. Ground based imagery fills a data gap between human observation (fine detail, low spatial extent, moderate temporal frequency) and satellite remote sensing (coarse detail, high spatial extent, low temporal frequency). Figure 8 illustrates a

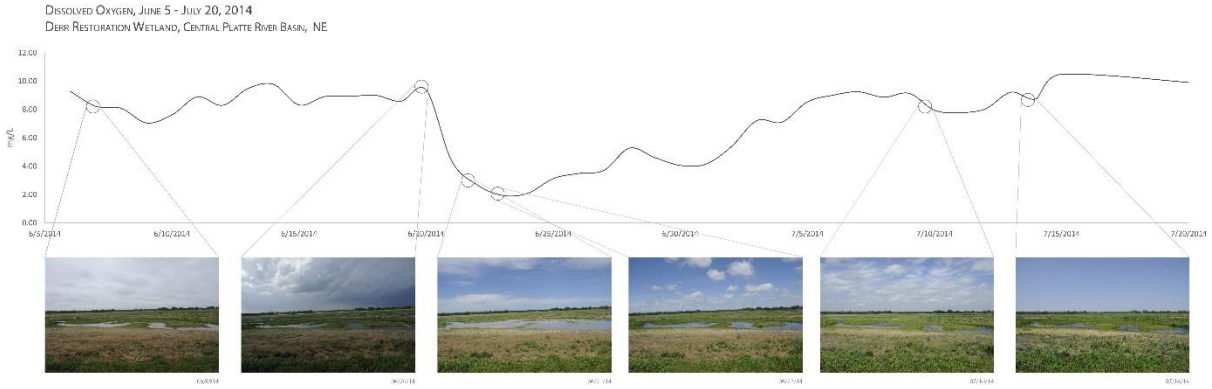
simplified portrayal of scaling up in spatial resolution from differing methods of data acquisition. Human observation often concentrates on a fine scale, such as detail of an individual species. Satellite, or even aerial imagery, documents a larger system at a birds eye view. Time-lapse imagery captures a landscape or community, substantiating a more continuous spatial alignment. Furthermore, although the oblique view captured by time-lapse can be challenging to quantitatively characterize, the perspective can be more interpretable, tangible, and relatable to public audiences and thus, aid in understanding.

Figure 9. Streamflow at Plum Creek Complex (PCC) from March to May of 2014. The hydrograph of an additional site downstream is illustrated by the blue line for reference.

Dams and diversions, engineered for human-use activities, have significantly impacted the natural flow regime of the central Platte River Basin, removing or retiming 70% of the historic streamflow over the last century (Zuerlein 2001). Altered timing, duration, and quantity of streamflow has impacted the habitat of endangered and threatened species, resulting in litigation and regulatory agreements. Located downstream from the Johnson No.2 hydropower plant operated by Central Nebraska Public Power and Irrigation District (CNPPID), site PCC experiences controlled and stabilized fluctuations in streamflow (Figure 9). In accordance with

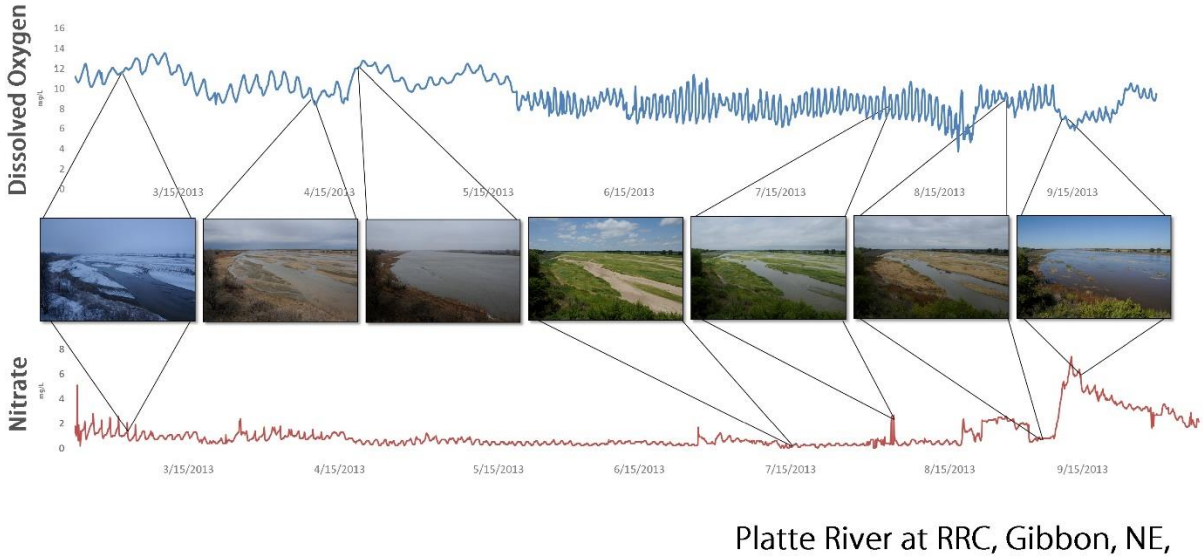
regulatory agreements, the Central Nebraska Power and Irrigation District is required to meet instream flow and environmental requirements for the stretch of river where PCC is located. This includes the cycling of surface water from March 18 to April 30 to decrease nightly influxes of river stage (CNPPID 2007, USFWS 2007). The engineered flow regime at PCC, illustrating human-controlled fluctuations and drastic variation in streamflow within short temporal intervals, oscillates approximately every four days from March 18 to April 30, and on a diel schedule from hydropower cycling in the beginning of March and May. The hydrograph of a location upstream of the control infrastructure is provided to visualize the dichotomy and contrast between sites and the impact of human engineering. The coupling of time-lapse imagery with the hydrograph at PCC enables contextual meaning and vivid visual changes. The time-lapse data sequence sets up a narrative framework, alluding to the controversy among federal agencies, environmental groups, industry, and individuals within a water-stressed landscape, exemplifying the complex dynamics of coupled social and ecological systems.

Figure 10. An example of validating anomalies or outliers within datasets by visually referencing time-lapse imagery. The plot is of dissolved oxygen levels in June 2014 at DRW.



Unaccompanied, time-series datasets and individual data points can be abstract and elusive to researchers and public audiences alike. As the natural world is complex and highly variable, ecological datasets can be difficult to deconstruct. Discrepancies or outliers can be challenging to examine and require further statistical scrutiny. Time-lapse imagery offers validation or reassurance, in addition to passive monitoring, to resolve these inconsistencies. For example, Figure 10 depicts daily averaged dissolved oxygen concentrations at DRW, a restored slough. At this location a stream gauge is not available. Measurements of rainfall can often be telling of aquatic fluctuations, however visual analysis of plots and correlation analysis did not provide additional information. Referencing the corresponding time-lapse imagery, the decline in dissolved oxygen on June 20, 2014, occurs with the observance of a flash pulse of high water inundation and thus, reaffirms what may have appeared as an outlier. For public audiences, the synthesis of graphics and time-lase can provoke contextual understanding of aquatic systems by providing tangible evidence and a visual setting. This framework can also encourage further discourse regarding chemistry, dissolved oxygen, turbidity, and pollutants.

Figure 11. Visible and Invisible Ecological Dynamics



The often indistinguishable association between visible landscape changes and water quality fluctuations, which are not observable to the human eye alone, can be visualized to provide insight into complex natural systems (Figure 11). The top graphic depicts hourly measurements of dissolved oxygen from March to September of 2013, where a difference in dissolved oxygen is evident between spring (March/April) and late summer (July/August). Broadly, the observed divergence is commonly an attribute of seasonality, in addition to interrelated factors. The generally decreasing trend in dissolved oxygen is commonly a factor of temperature; as water temperature increases, the solubility of gas decreases, and thus, the retention of dissolved oxygen is reduced. The diel variation, observed in the graph as moderate oscillations in March and more drastic oscillations in July, is demonstrative of ecological dynamics associated with seasonal activity- most predominately primary productivity. Photosynthesis, the underlying biological process is conceptually represented by time-lapse imagery as the greening up of vegetation. The more drastic oscillations observed in July and

August is suggestive of aquatic photosynthetic activity generating dissolved oxygen during the day. As vegetation relies on the sun for energy, photosynthesis ceases at night, and thus the dissolved oxygen levels decrease.

Furthermore, the time-lapse data sequence in Figure 11 presents a framework encompassing a holistic systems perspective to illuminate the interconnectedness of a stressed watershed; intertwined dynamics varying in time, frequency, association, and visibility. For example, seasonality occurs at a consistent yet moderate temporal scale observed by the human eye, but is easy to overlook due to the slow rate of transitional occurrence. Time-lapse imagery's capacity to compress time elucidates this subtle phenomenon. Paired with data visualizations, the association among abiotic and biotic changes of varying visibility are depicted, which can be observed in alignment with seasonality; temperature, vegetation phenology, and variations in water chemistry. Moreover, Figure 11 further exemplifies a systems perspective of a stressed watershed by depicting the increase in nitrate concentrations in relation to the increase in streamflow in September of 2013. This visual illustration frames a narrative to discern the interconnected dynamics of terrestrial-aquatic systems, land-use impacts, drainage through a watershed, and the implications of human-use activities on water quality and natural systems.

Figure 12. River Morphology

As a ground-based monitoring device, time-lapse imagery acquires synoptic field data, including fluvial morphology illustrated in Figure 12. Imagery can be used to assess flow, sediment transport, erosion, and additional topographic data (Chandler et al. 2002). The Platte River is a dynamic and braided prairie river system, and thus, requires a versatile method to collect data. This is evident in Figure 12 as time-lapse imagery documented and visualized the variability in streamflow and changing physical characteristics of the river bank. The capacity to observe hydrology and its influence on river morphology depicts the powerful force of water, its ability to shape both aquatic and terrestrial systems, and alludes to the interactions between social-ecological systems.

Discussion

Across multiple spatio-temporal scales, environmental change and human impacts on the natural world has increased the importance of monitoring and understanding ecosystems (Brown et al. 2011). Innovative methods of documentation and knowledge-sharing are needed to conserve ecosystems and sustain our natural resources. Our results demonstrate the duality of digital time-lapse imagery to function as an expressive aesthetic and as a means of observational evidence. The versatility in applications holds potential to capture and illustrate changing

dynamics and provide insight into and aid in the understanding of natural systems. Time-lapse data sequences visually presented both visual and invisible changes over time, which offers the potential to contribute observational knowledge with the intent to enrich understanding; for researchers to further comprehend anomalies, scientists to inform policy, land-stewards to guide management, teachers to augment learning objectives, and informal educators or organizations to raise awareness and interest in environmental issues.

Utilizing digital time-lapse cameras as passive sensors enables data collection at a range of temporal and spatial scales, as our results indicate the proficiency of time-lapse to characterize vegetation phenology and quantify water inundation. Time-lapse imagery bridges the spatial scale between satellite imagery and in-person observations (Figure 8), while extending the temporal frequency of data acquisition (Figure 7). As global climate change disrupts the timing and synchronicities which organisms depend on for survival (Johansson et al. 2015), the documentation of abiotic and biotic responses at multiple scales of time and space is a key part of managing and mitigating for the impacts of a globally changing climate (Visser & Both 2005). The high-resolution, temporal-capabilities, ease of use, and ability to archive and reference imagery for future examination, has contributed to the increasing utilization of time-lapse imagery in scientific research (Webb 2010). Employing camera systems to examine a river flood-plain, our results support the findings of previous studies demonstrating the value of time-lapse imagery in assessing vegetation phenology in forest (Richardson et al. 2009, Sonnentag 2012), agricultural (Gitelson 2002, Sakamoto et al. 2012), grassland (Inouye et al. 2014), and glacial systems (Byers 2007). Moreover, results from image-analysis of wetland water inundation suggest that time-lapse cameras are capable of documenting systems previously

unmonitored or due to constraints, infrequently measured. For example, hydrologic equipment such as stream gauges, can require in-person measurements, familiarity with scientific tools and methodologies, and furthermore, are limited in their application as they are designated for one use. The application of time-lapse imagery to monitor aquatic systems can provide near-continuous data collection of hydrologic changes, in addition to various other datasets such as vegetation encroachment or sandbar dynamics, while simultaneously offering visual confirmation of landscape changes. Our preliminary findings are suggestive of the capabilities of time-lapse imagery to augment data collection and increase the spatial and temporal capacity to quantify system changes.

In addition to expanding monitoring scales, the proficiency of time-lapse imagery to document change makes it a powerful communicative tool. Communication with non-scientists is necessary to sustain support for scientific research and an essential catalyst to foster sustainable behavior (Sunderland et al., 2009). Progress towards solutions to many environmental challenges requires the attention and awareness of diverse societal actors. Imagery compels society to face environmental issues and the integration of time-lapse imagery with data visualization merges the aesthetically and emotionally captivating with logic and fact to further blur the line of separation between art and science. The capacity for imagery to provoke self-examination, elicit emotional connections, tell a narrative, and conjure a response, while concurrently capturing change and establishing a baseline, has been a pervasive influence on society and the perception of the natural world (Ward 2008, Thomsen 2015, Myers 2006). Reinforced with data graphics, time-lapse data sequences blend aesthetic and fact, appealing to both reason and emotion, while connecting facts to tangible context and a visible setting.

Time-lapse data sequences take advantage of the prevalence of online environments to improve access, increase aesthetic lure, and inform diverse audiences. When presented in a digital format, time-lapse data sequences incorporate interactive elements allowing for flexibility and efficiency to transcend the static limitations of traditional communicative approaches. Contrastingly, traditional media, such as newspaper and hard copies, is often inherently static, and thus, constraining, representationally limiting, isolated from key societal actors, and inadequate to overcome complexity and design challenges. An author or editor is often required to make a decision in regards to translating a fact or message in static media; depict one moment in time and space or generalize a concept to an average- restricting the scale to one spatio-temporal point and limiting the potential to communicate process and complexity. The malleability of time-lapse data sequences does not adhere to a rigid format and is capable of representing complexity and transitioning among time and space, a key factor in exploring and assessing natural systems. This structure enables content to be extended in novel ways, organized in an interactive framework, and viewed as various arrangements by way of animation, dynamic elements, or hyperlinks (Eveland 2003). User-defined actions allow individualized pace to view or reexamine content (skimming vs. in-depth reading) to aid in comprehension. This interactivity can facilitate multidimensional exploration, selectivity, and engagement (Liu & Schrum 2009, Vervoot 2010) to create explanative environments, encourage pattern recognition, make inferences, and foster understanding of the interconnectedness of content and concepts (Eveland, 2002, Liu & Schraub 2009, Andienko 2010). Facilitated by interactivity, active engagement has been shown to positively impact learning and learner satisfaction (Liu & Schrum 2009), in addition to increasing inquiry and interest in scientific-

related fields (Chou et al. 2012, Zheng et al 2014). As a generational difference in communication is evident, where younger generations are technologically sophisticated, the advancement of interactive approaches has become increasingly necessary as younger generations may reject traditional and monotonous educational methods (Jonas-Dwyer & Pospisil 2004).

Digital time-lapse data sequences enables flexible access for knowledge-sharing to go beyond traditional learning approaches. Portable devices such as tablets, laptops, and cellphones, have presented opportunities for mobile knowledge-sharing and engagement through a nature-technology interface and have emerged as a commonly used tool for integrative indoor/outdoor experiences and mobile learning (Hwang & Wu 2014). Recent studies have found that mobile electronics are pedagogically beneficial, and can enhance a user's experience, knowledge, and motivation (Park 2011, Hwang & Wu 2014), to aid in generating a sense of place and act as a catalyst to foster sustainable action. Further knowledge, awareness, and association of a place can assist in developing a deeper connection as the concept of place is a coconstructed process and perspective of synergistic values, feelings, and derived meaning, further knowledge and awareness can assist in developing a deeper connection (Adams & Gynnild 2013).Time-lapse data sequences delivered by a portable digital platform can connect individuals by facilitating context awareness and content adaptivity. Context awareness, the familiarity with a physical location, situation, or people, is achieved through visually immersing individuals or audiences into a place through graphics and imagery connected to their physical location. Content adaptivity, the ability to direct materials and information to appropriate individuals (i.e. age, learning objective), is enabled through the malleability of time-lapse data sequences and wide

range of applications and capabilities to tailor narration and learning experiences (Pea et al. 2012). For example, an individual can visit a physical location such as a park or nature center, and through wire-less internet, cell-service, or pre-loaded devices can access historical evidence and/or real time data to guide explorative learning, observe changes over time, and create relational understanding. By digital access to time-lapse data sequences, the connection to the park can continue even after an individual leaves the physical location to enable a more in-depth experience. This technology-nature interface presents opportunities to network experiences and engage outside audiences. This could be a student visiting a location on a field trip, staying engaged with the site while at school, and then sharing their connection to the place at home. The portable applications of digital time-lapse sequences offers opportunity to strengthen connection and contribute to local knowledge bases, a consideration for understanding social-ecological systems (Gerhards & Schaffer 2010).

Digital time-lapse imagery offers a technique capable of dual purposes; as a tool to monitor systems, document change, obtain quantitative data and fill a gap in scale, and through digital time-lapse sequences, as a communicative medium coupled with data visualization to inform audiences, spark interest, facilitate novel perceptions, and provide insight into natural systems.

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Figures

Figure 1: Platte River Basin watershed extending from Colorado and Wyoming into Nebraska.

Figure 2. Map of study locations; Plum Creek Complex (PCC), Rowe River Channel (RRC), and Derr Restoration Wetland (DRW) in the Central Platte River Basin of Nebraska.

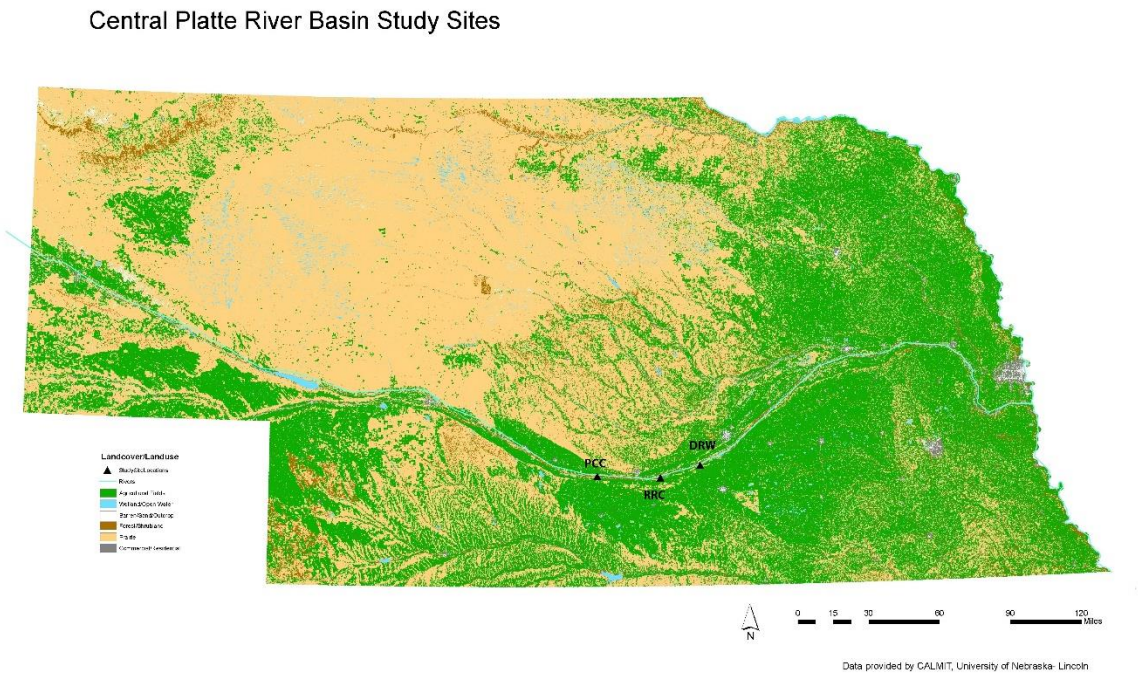


Figure 3: Close up of time-lapse camera station with solar panel and additional monitoring equipment in the central Platte River Basin of Nebraska.

Figure 4: Image analysis of time-lapse imagery to classify surface water inundation at DRW.

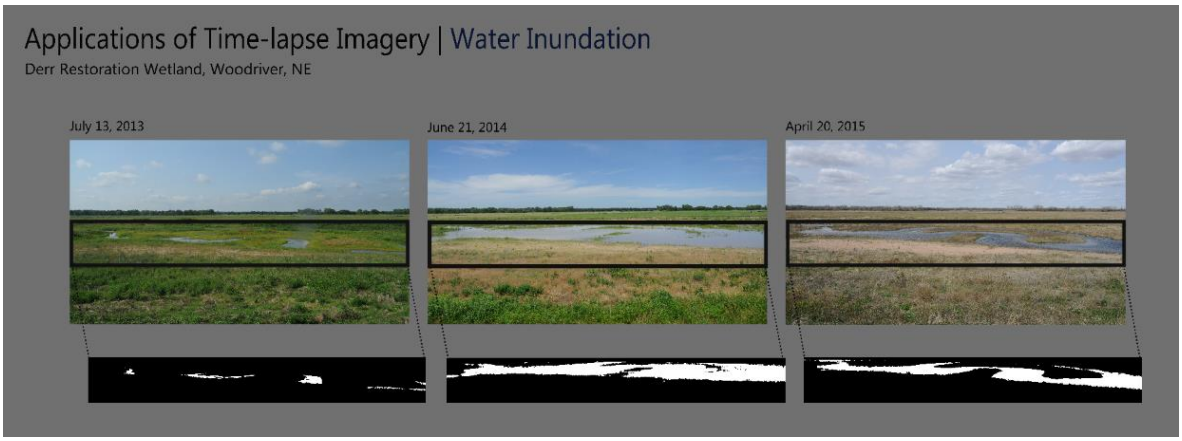


Figure 5: Characterization of vegetation phenology at three sites, Derr Restoration Wetland, Plum Creek Complex, and Rowe River Channel in 2013, 2014, and the spring of 2015. Results were obtained from image analysis using the Green Chromatic Coordinate vegetation index.

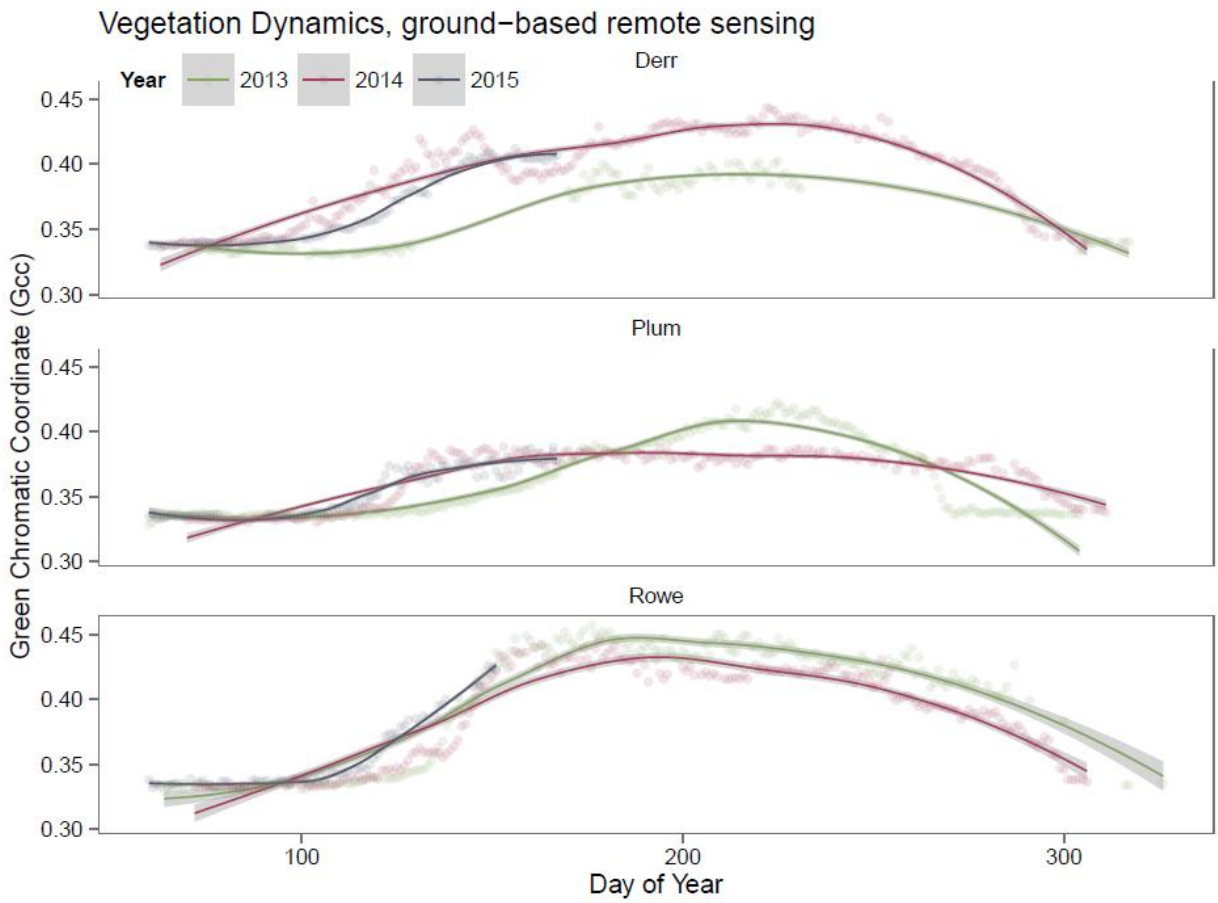
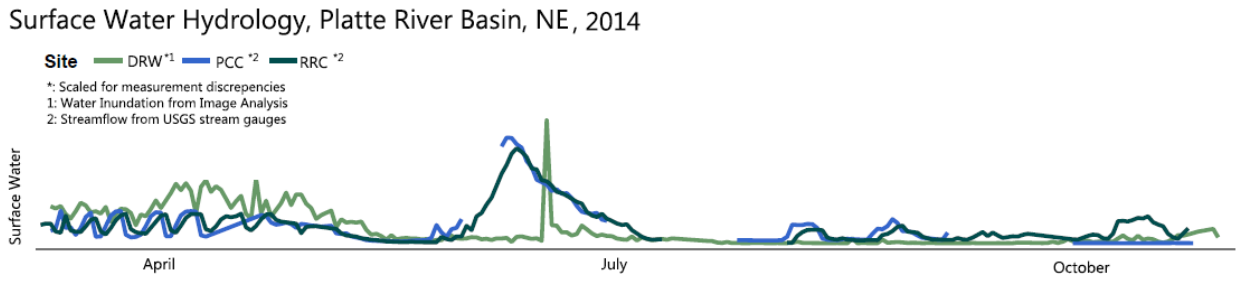


Figure 6: Surface Water Hydrology at three sites, DRW, PCC, and RRC in the central Platte River Basin of Nebraska in 2014. Data has been scaled to account for discrepancies in measurements. Surface water at DRW was assessed via image analysis of time-lapse imagery. Streamflow data was acquired from stream gauge stations.



CHAPTER 3: TEMPORAL SURFACE WATER DYNAMICS OF A STRESSED RIVER BASIN IN THE GREAT PLAINS

Introduction

River systems are inherently complex, a function of natural and anthropogenic dynamics interacting across time and space. Human-use activities have significantly altered the quality and quantity of water in rivers, which can affect aquatic biodiversity and ecosystem services (Brunner et al. 2000, Vörösmarty et al. 2000, Meybeck 2003). Stress on water resources is predicted to increase as a result of land and water-use changes, human population growth, and global climate change, making sustainability and management of freshwater resources challenging priorities (Poff & Richter 2012). This chapter couples data derived from time-lapse imagery with water quality monitoring data to identify temporal fluctuations in surface water dynamics and explore new integrative approaches to enhance our understanding of the scales and complexities of river systems.

Temporal variability of surface water dynamics, including water quality and flow regime, can be broadly characterized by diurnal (temperature) or seasonal trends in response to predictable environmental (i.e. seasons) or anthropogenic (i.e. dam releases) factors. River systems and the surrounding terrestrial landscape are highly interconnected, and therefore fluctuations in water quality and quantity are an accumulated reflection of the precipitation/surface runoff, land cover, temperature, human-use impacts, and stochastic events across the watershed (Williams et al. 1995, Thurman et al. 1991, Frey 2000, Capel and Larson 2001, Stueber et al 2003, USGS 2011). Thus, changes or perturbations to either can influence the other, the organisms they support, and the numerous regulatory, provisioning, and cultural

services they provide (Griffith et al 2002, England & Rosemonde 2004, Fischer et al. 2009, Davis et al. 2014).

The Platte River Basin is a key example of an over-appropriated, complex and human-dominated river basin. One of the most significant watersheds in the Great Plains (Williams 1978), the Platte River in Nebraska and its tributaries, the South Platte in Colorado and North Platte in Wyoming, have undergone extensive engineering and development, resulting in changes that have redefined the river (Eschner 1981, Strange 1999). Historically, the hydrograph of the Platte River Basin was dominated by climatic events and seasonal pulses, with peak flows driven by snowmelt in the spring (Snow & Spalding 1988), however, water-provisioning infrastructure for industrial, agricultural, and domestic-use has removed or retimed 70% of the Platte's natural flow regime directly and indirectly altering the morphology and hydrology of the watershed (Williams 1978, Aiken 1999) and thus, affecting the historic structural, chemical, and biological characteristics. Furthermore, these changes have impacted critical wildlife habitat (Eschner 1981, Johnson 1994, Swanson et al. 1998), prompting legal litigation and recovery plans to manage land and restore adequate stream flows for federally listed species, including whooping cranes (*Grus Americana*), interior least terns (*Sterna antillarum*), and piping plovers (*Charadrius melodus*).

In Nebraska, land and water use is dominated by agricultural activity, which can contribute to decreases in water quantity, declines in water quality, and is a notable source degradation to freshwater systems (Frenzel et al. 1998, USEPA 2009, Gharibi et al. 2011). Approximately ninety percent of Nebraska's water consumption is for irrigation (USGS 2005), and albeit the main source is groundwater wells, the hydrology of the river is linked to the

alluvial aquifer, where excessive withdrawals result in streamflow depletion (Chen 2007). The use of agrichemicals, such as herbicides and fertilizers, contribute to high concentrations of pollutants and nutrients, which lead to eutrophication, a leading cause of impairment in Nebraska's waters (USEPA 2014). Aquatic life requirements, such as dissolved oxygen, and the recreational and aesthetic value of freshwater resources, can be degraded by excessive algal growth caused by nutrient enrichment. Impairments to water resources can have major economic, health, and ecological repercussions (Dodds et al. 2008, Storrs and Keisecker 2004, Hayes 2006, Comfort et al. 1996). Therefore, using an integrative approach coupling time-lapse imagery and water quality sampling to identifying surface water variability can enhance our understanding of river system dynamics; a critical step for sustainability, management strategies, and conservation initiatives of water resources.

Given, these challenges, the primary objectives of this chapter are focused on methodological applications, specifically to:

1. Explore the utility of time-lapse imagery for monitoring and data acquisition of aquatic systems.
2. Characterize temporal water quality fluctuations using multivariate time series analysis.
3. Assess surface water patterns.
4. Examine the use of time-lapse imagery to inform management of aquatic resources.

Methods

Study Sites

The study region is a ~90km section of the central Platte River Basin often referred to as the Big Bend Reach, and extends from Lexington, Nebraska, USA, eastward to Grand Island, in

south central Nebraska. A leading agro-ecosystem, agriculture of largely maize-soybean in rotation, is the dominant land cover, accounting for ~49% of land use in the Big Bend reach (Brei et al. 2008). Grasslands cover an additional 24%, followed by 15 % for wet meadow, development, and riparian woodland. Reduced stream flows in the Platte River have allowed vegetation growth on surrounding riparian areas, resulting in an abundance of invasive species and woody encroachment such as Purple loosestrife (*Lythrum salicaria),* Common Reed (*Phragmites*), Eastern Red Cedar (*Juniperus virginiana*), and Russian Olive (*Elaeagnus angustifolia*).

Three study sites, Plum Creek Complex, Rowe Sanctuary, and Derr Restoration Wetland, are located within Big Bend reach of the Central Platte River Basin (Figure 1). Plum Creek Complex (PCC) is the furthest west research location, positioned at the intersection of the Platte River and the 183 Bridge in Buffalo County, Nebraska. The channel is approximately 200m wide after it converges from multiple braided channels into one main passage. Rowe Sanctuary (RCC), in Gibbon, Hall County, Nebraska, is maintained by the National Audubon Society and located on the Platte River's south bank of the central channel. The width of the river channel at this location is roughly 300m. Vegetation on the sandbars and riparian area are removed to maintain habitat for wildlife. Derr restoration wetland (DRW), the eastern most research site, is located on a section of the Platte River Prairies tract of land owned and managed by The Nature Conservancy (TNC) in Wood River, Nebraska. The site is less than a mile south from the Platte River and consists of a wetland slough with a meandering stream channel, restored in 2011 from a sand and gravel mining pit. The surrounding TNC land is maintained as native prairie and bordered by privately owned agricultural fields.

Water Quality Sondes (Passive Sampling)

Passive measurements of temperature, dissolved oxygen, pH, and specific conductivity were recorded at each site with a Manta 2 (Measurement Specialties) multiprobe sonde at hourly intervals (hereon referred to as 'passive' sampling/data, Table 1). The equipment was installed in 2013 and 2014 from early spring, when ice-jams cleared, until late fall, when ice began to form. Individual sondes were powered by an external waterproof battery pack and enclosed in a protective case of perforated PVC. A flotation device was attached to the unrestrained end which prohibited the equipment from dragging on the river bed and allowed standardization of depth at which the sondes took readings (~15cm from water surface). At RRC and PCC the sonde was chained in place to a bridge (Figure 3) and at DRW the equipment was secured with wire to a post. Measurements were logged continuously every hour. Manta sensors were manually downloaded in the field and calibrated every two to four weeks. Additionally, the sensors were cleaned to remove biofilms and the reference electrode (pH and ISE measurements) was maintained every two to four weeks.

Water Grab Samples (Active Sampling)

Water quality measurements were obtained actively by grab sample at discrete intervals approximately once a week from March to October 2014 (hereby referred to as 'active' sampling/data, Table 1). Surface water samples were collected at RRC and DRW from the center of flow at a depth of 15cm. Samples were collected in 250 mL polyethylene bottles for nitrate/nitrite, total phosphorous, orthophosphate, total organic carbon, total Kjeldahl nitrate, total phosphorous, and ammonia and preserved using sulfuric acid (H2SO4) until analyzed.

Additionally, samples were collected in 1-liter amber glass solvent bottles for turbidity and a scan of pesticides (only Atrazine and its metabolite, DEA, were included in this study). Samples were transported on ice to the University of Nebraska- Lincoln Water Science Center (watercenter.unl.edu) for analysis in accordance with the U.S. Environmental Protection Agency (http://www.epa.gov/) and the Standard Methods for the Examination of Water and Wastewater (http://www.standardmethods.org/) where applicable.

Streamflow

Streamflow data was downloaded from USGS streamflow-gaging stations (Table 1). Discharge measurements corresponding to RCC was obtained from station ID 06770200 near Kearney, Nebraska (Latitude 40°41'08", Longitude 99°26'20" NAD27). Data from Site ID 06768025 near Overton, Nebraska (Latitude 40°40'44", Longitude 99°29'21" NAD83) corresponded to sampling at PCC.

Estimates of Water Inundation from Time-lapse Imagery

The hydrologic regime of the DRW, although influenced by the hydrology of the Platte River, is driven by a ground-water fed stream, and has varying discrepancies in system characteristics and water contributions such as surface water runoff, precipitation, evapotranspiration, vegetation, and surface area. Therefore, an innovative technique was necessary to assess the amount of surface water over time at the wetland. Water inundation was quantified using digital time-lapse imagery and pixel analysis. A high resolution DSLR time-lapse camera was installed overlooking the wetland as part of the Platte Basin Timelapse project

(PBT). A red-green-blue (RGB) color channel image was captured every hour between sunrise and sunset. The images were automatically uploaded to PBT's 1.5 terra-byte image library and selected through Phocalstream, software technology developed by the Jeffrey S.Raikes School for Computer Science and Management at the University of Nebraska – Lincoln. Three images a day were selected between the hours of 10:00 and 14:00 for standardization and vetted for variations within the frame of view (weather, spider web, etc.). To extract water inundation, images were batch analyzed in Image J (Image J software, NIH, Bethesda, Md., U.S.A.), an image analysis program created by the National Institute of Health, using a custom script modified from a microscopy technique in the health sciences (Hadi et al. 2011, Schneider et al. 2012, Hakonen et al. 2014). RGB images were transformed to the cylindrical hue-saturation-value (HSV, also called HSB; brightness) color space for more accurate color statistics (Chang et al. 2010). Hue is the spectral property of a specific color, saturation is the intensity perception of a color, and value denotes the perception of brightness of a color. The hue slice of the HSV stack was cropped to a region of interest (ROI) which encompassed the most wetland area and discarded the terrestrial landscape to reduce errors associated with variations between images (Figure 4). The ROI was converted to a binary (black and white) image where pixel values were 1 or 0. The level of thresholding was determined by an automatic function that divided the image into background (0) and objects (1) by producing a test threshold and calculating the average of pixels above and below the test threshold. The area statistics were calculated using the 'Measure' function selected for area fraction with an overlaying mask. The resulting images were checked for accuracy by visual comparison of the original image and the produced mask. Results were

output to a CSV file organized by file-name and date. The final data from image-analysis is numerically representative of the percentage of pixels in the ROI classified as water.

Multivariate Time-series Analysis

To assess temporal water quality dynamics of the river basin I employed a multivariate time-series modeling approach based on asymmetric eigenvector maps (AEM) (Borcard and Legendre 2002) with a redundancy analysis (RDA) component (Angeler et al. 2009). The approach is a powerful tool for interpreting variations in water quality, as it deconstructs the linear temporal trends and is capable of identifying mechanisms interacting at varying sinusoidal cycles (Angeler et al. 2009). Analyses were run separately for each location. Active water quality data was acquired at weekly intervals and passive water quality data was measured at hourly intervals and thus, for this analysis, data was standardized by selecting the date and time of passive data that corresponded with the timestamp of the active data. All water quality parameters were scaled to account for the differences in measurement units but did not need to be normally distributed due to the combination of ordination, regression, and the permutation procedure used in the analysis (Legendre & Legendre 1998).

Using AEM analysis, a set of orthogonal temporal variables was extracted from a vector of sampling dates. The vectors consisted of 32 time steps at RRC and 33 time steps at DRW (i.e. sampling weeks) and both generated 16 AEM variables representing specific temporal pattern and scale. The first AEM variable is a linear model and successive variables proceed from slow (AEM 1) to increasingly rapid frequencies (AEM 16) (Figure 5). The resulting temporal variables derived from AEM were then used in RDA analysis as explanatory variables with

thirteen water quality parameters as response variables. A model was developed for each site through a forward selection procedure which retains variables with statistical significance. The AEM variables retained in the parsimonious models were then used in RDA to construct temporal patterns from the water quality parameter matrices. Parameters with similar patterns within the water quality parameter x time matrix were grouped together and a collective trend was generated through linear combination of AEMs.

Permutation tests determined the significance of the temporal patterns of grouped water quality parameters. Significant canonical axes were related to each temporal fluctuation pattern and their relevance quantified using adjusted R^2 values. Linearly combined (lc) score plots are produced to illustrate the spectral decomposition of temporal relationships between time steps and water quality parameters of the RDA axis derived from the significant, linearly combined AEM variables. The number of temporal scales at which water quality fluctuates is revealed by the number of significant canonical axes (Angeler et al. 2011). Multivariate time-series analysis was conducted using the 'quick PCNM' function in the PCNM package (Legendre et al. 2013) and 'aem.time' function in the AEM package (Blanchet and Legendre 2013).

The strength at which individual water quality variables contribute to the temporal structures was assessed using Spearman's rank correlation analysis, which evaluates the relationship between the linear combination scores identified from the canonical axes and the water quality measurements.

Statistical Analysis

Statistical analyses were conducted in R 3.0.2 (R Development Core Team, 2012). Correlation analysis was used to assess the relationship between passive water quality variables. For the analysis, daily averages were calculated from hourly measurements. Passive sampling was examined to identify temporal dynamics of water quality during the study duration of two years, 2013 and 2014, utilizing visualizations and descriptive statistics.

Results

A total of 924 passive samples and 65 active samples were analyzed between March 2013 and October 2014 (Table 2, Figure 6). Significant relationships ($p<0.05$) were identified using Spearman's rank correlation analysis and reported below (Figures 8,9,10).

Passive Data

Visual assessment of passive water quality monitoring at PCC, RRC, and DRW demonstrated fluctuations associated with seasonality and interconnected relationships among variables. Surface water fluctuations at all three locations exhibited a variable influx of water (streamflow/water inundation) during the spring season, a gradual decrease into the summer period, and slight variability with relatively low streamflow into the fall. However, a substantial peak in water was evident at all study sites in June 2014, coinciding with increased precipitation. Graphical comparison revealed a lag in peak streamflow between sites as maximum discharge was reached at PCC on ~06/10/2014, RRC on ~ 06/14/2014, and DRW on ~06/20/2014; a range of approximately 10 days. In addition, DRW exhibited the least amount of temporal variability in

water inundation throughout 2014. Streamflow at RRC ranged from 2 to 6610 CFS with a mean of 811 CFS (±1100) and at PCC ranged from 12 to 12444 CFS with a mean of 1200 CFS (± 1934). At PCC, streamflow exhibited a statistically significant, although moderate, correlation with pH *(*rho =0.45) and specific conductivity (rho=0.36). Water Inundation at DRW ranged from 0.47 to 15.3 with a mean of 6.99 (±4.5). At DRW, water inundation was significantly negatively correlated to Julian Day (rho= -0.71) and water temperature (*rho*=-0.59). There was no statistically significant association between streamflow and temperature (rho=-0.02, -0.016, p>0.05) at either PCC or RRC.

Overall, water temperature in the Platte River Basin ranged from 1.61 to 31.38° C with an overall mean of approximately 18° C (±6.8) during the study period. The river system reached colder temperatures (1.61° C) compared to the wetland (4.26° C). A positive correlation was found (p<0.05) between temperature and Julian day (rho=0.53 (PCC), 0.42 (RRC)) at PCC and RRC.

At all study locations, a negative relationship was found between water temperature and dissolved oxygen (rho =-0.72, -0.84, -0.79). Dissolved oxygen observations at PCC and RRC ranged from 5.53 to 12.93 mg/L with a mean of 8.6 (±1.5) mg/L. DRW had greater variation in dissolved oxygen, ranging from 1.19 to 12.9 mg/L, but the mean was similar at 8.53 mg/L (±2.4). Julian day and dissolved oxygen were found to be negatively correlated at DRW, PCC, and RRC (rho=-0.38,-0.44, -0.52). A positive relationship was found between dissolved oxygen and water inundation at DRW (rho=0.56). Interestingly, there was a statistically significant but weak to moderate association between dissolved oxygen and streamflow at RRC (rho =0.32), but no significant correlation was identified at PCC (rho =-0.14, p>0.05).

At PCC and RRC, pH ranged from 7.65 to 9.16 with a mean of 8.44 (±0.32) at PCC and 7.36 to 8.97 with a mean of 8.36 (±0.29) at RRC. The pH of DRW ranged from 7.4 to 8.75 with a mean of 8.15 (±0.28). All research locations showed a negative correlation between Julian day and pH (rho = -0.47, -0.88, -0.62). pH measurements at DRW were found to be significantly associated with water inundation (rho=0.45), specific conductivity (rho=0.44), and dissolved oxygen (rho=0.47). At PCC, streamflow and pH were significantly correlated (rho =0.45) but no statistically significant relationship was identified at RRC. pH levels at PCC and RRC were frequently higher than DRW.

Specific conductivity ranged from 572 to 1143 μS/m with a mean of 1029 μS/m (±87) at DRW. Measurements of specific conductivity at RRC ranged from 250 to 1117 μS/m with a mean of 820 μS/m (±187) and at PCC from 548 to 1207 μS/m with a mean of 878 μS/m (±132). Specific conductivity at DRW was significantly correlated to water inundation (rho =0.69), dissolved oxygen (rho=0.64) and negatively correlated with water temperature (rho =-0.58) and Julian day (rho=-0.50). A statistically significant relationship between specific conductivity and dissolved oxygen (rho =0.54) and a significant negative relationship between specific conductivity and Julian day (rho =-0.91) were found at RRC. At PCC, specific conductivity was significantly but weakly correlated to streamflow (rho =0.36), and negatively correlated with Julian day (rho=-0.59).

Active Data

Active water quality sampling at RRC and DRW exhibited temporal trends (Figure 11), among a wide array of ranges and means for data sampled in 2014 (Table 2, Figure 14). Spearman's Rank Correlation analysis revealed significant correlations ($p<0.05$) for water quality parameters at both DRW and RRC and are presented below (Figures 12, 13).

Nitrate concentrations demonstrated similar trends in the river channel and wetland, reaching maximum concentrations in March, and peaking again in May. During active sampling from March to November of 2014, the mean nitrate concentration at RRC was 0.74 mg/L (±0.64) and ranged from 0.016mg/L to 2.33 mg/L. The mean nitrate concentration during the study period at DRW was slightly lower at 0.29 mg/L (±0.51) with a minimum of 0.018 mg/L and a maximum of 2.05 mg/L. At both sites, a negative correlation was found between nitrate and water temperature (rho=-0.66 and -0.64) and nitrate and Julian day *(*rho=-0.61, -0.51) and positively correlated with dissolved oxygen (rho=0.52, 0.47). At DRW, nitrate was correlated with water inundation (‘streamflow’, rho=0.63), but no statistically significant association was found between streamflow and nitrate at RRC (rho=-0.03).

At DRW, ammonia ranged from undetectable concentrations to 0.551 mg/L with a mean of 0.144 mg/L (±0.13) and at RRC, ammonia ranged from 0.0 mg/L to a maximum of 0.323 mg/L, with a mean of 0.0757 mg/L (±0.08) during the study period. At both sites ammonia was found to be negatively correlated with Julian day (rho=-0.75, -0.48), turbidity (rho=-0.45, -0.36) and total organic carbon (rho= -0.58, -0.67). At RRC, ammonia was significantly associated with nitrate (rho=0.39) and dissolved oxygen (rho=0.54).

Atrazine was detected in samples at both locations. Atrazine concentration at RRC ranged from a minimum of 0.0 ppb and a maximum of 0.29 ppb with a mean of 0.0759 ppb (±0.06). The concentration of atrazine was found to be higher at DRW, ranging from 0.12ppb to 0.76ppb, with a mean of 0.248ppb (±0.12). At both locations, atrazine was significantly correlated with temperature (rho=0.58, 0.61) and negatively associated with total organic carbon (rho=-0.46,-0.55) and dissolved oxygen (rho=-0.39, -0.6). Atrazine and DEA were found to be

statistically significant and highly correlated at RRC (rho=0.76), but no statistically significant relationship was found at DRW (rho=0.35, p>0.05). At DRW, a significant correlation was found between atrazine and phosphorus (rho=0.62), but no statistically significant relationship between atrazine and phosphorous was found at RRC. During the study period, atrazine was present in all water samples (n=33/33) obtained at DRW, and 0.75 of the samples collected at RRC (n=24/32).

Results revealed that during the 32 weeks of sampling at RRC and 33 weeks at DRW, DEA was present in all water quality samples. At DRW, DEA reached a maximum concentration of 0.44ppb and a minimum of 0.12ppb with a mean of 0.263ppb (±0.06). The maximum DEA concentration at RRC during the study period was 0.14ppb, the minimum was 0.06ppb, with a mean of 0.0825ppb (±0.02). At DRW, a statistically significant positive correlation was found between DEA and water inundation (rho=0.67), and a significant negative correlation was found between DEA and Julian day (rho=-0.72). At RRC, DEA was found to significantly correlated to water temperature (rho=0.53).

Phosphorus observations ranged from 0.01 to 0.34 mg/L with a mean of 0.08 mg/L (±0.09) at DRW, and from 0.02 to 0.36 mg/L with a mean of 0.13 mg/L (±0.08) at RRC. At both sites, phosphorus was significantly correlated with turbidity (rho=0.52 and 0.61). At DRW, a significant correlation was found between phosphorous and water temperature (rho=0.69), phosphorous and atrazine (rho=0.62) and a negative correlation was found between phosphorous and dissolved oxygen (rho=-0.74).

The mean concentration of orthophosphate at DRW was 0.03 mg/L (±0.05), with a range from 0 to 0.28 mg/L. The mean concentration at RRC was 0.04 mg/L(±0.02) with a range from

0.01 to 0.12 mg/L. Orthophosphate was found to be significantly negatively correlated with temperature (rho=-0.56) and nitrate (rho=-0.45) at RRC, but no significant correlation was observed at DRW.

Multivariate Time-series Analysis

Time-series modeling of water quality measurements in the Platte River Basin identified significant temporal frequencies occurring at both DRW and RRC during 2014 (Figures 16,17). Overall, RDA models explained 59% of the adjusted variance of water quality dynamics at DRW, and 71% of the adjusted variance at RRC. RDA1 at DRW accounted for 27% of the adjusted variance, and RDA1 at RRC accounted for 31% of the adjusted variance.

At both sites, linear combination scores analyzed using Spearman's Rank Correlation revealed significant intra-site and inter-site associations among temporal fluctuations. Within the research sites, no correlation was found among the RDA models ($p<0.05$). Between sites, a significant and highly correlated association was found between the first RDA at DRW and the first RDA at RRC (rho=0.84). A negative correlation was found between the second RDA at DRW and the second RDA at RRC (rho=-0.72). The AEM eigenfunctions selected through forward selection to derive the RDA's through linear combination exhibited differences in sinusoidal waves between sites. At DRW, V1,2,3,6,12,and 13, were selected and at RRC V1,2,3,7,5,10,4, and 9 were selected, with lower ranking values referring to longer/slower fluctuations in time and higher values referring to more frequent fluctuations.

Water quality variables contributing to the temporal structures were identified in the RDA analysis, and Spearman's Rank Correlation analysis revealed significant correlations between the RDA's and contributing parameters (Figures 16 & 17). At DRW, the first RDA was significantly positively correlated ($p>0.05$) with Julian day, and turbidity, and negatively

correlated with total organic carbon, pH, water inundation, ammonia, and DEA. The second RDA was positively correlated with dissolved oxygen, nitrate, total organic carbon, and water inundation, and negatively correlated with orthophosphate, ammonia, TKN, atrazine, temperature, and phosphorous. A positive correlation was found at DRW between the third RDA and water inundation, and a negative correlation between the third RDA, nitrate, and Julian day. At RRC, a positive association was found between the first RDA and total organic carbon, turbidity, Julian day, and phosphorous, and the first RDA was negatively correlated with DEA, ammonia, atrazine, and nitrate. The second RDA at RRC was correlated to temperature, atrazine, DEA, and Julian day, and a negative association was found between the second RDA and dissolved oxygen, orthophosphate, nitrate, and ammonia. The third RDA was negatively correlated with TKN and nitrate, and positively correlated with water inundation. The fourth RDA at RRC was negatively correlated with streamflow, phosphorous, and atrazine.

Discussion

The modification of freshwater systems, a result of anthropogenic stressors such as land and water-use changes, human population growth, and global climate change, have had significant ecological impacts, and therefore, emphasize the importance of monitoring, management, and understanding the dynamics of stressed watersheds. Time-lapse imagery offers a versatile method of data collection, while concurrently providing visual documentation of landscape changes. The efficiency of standard stream flow monitoring technology is limited to one application, and requires personnel familiar with scientific tools and methodologies. In contrast, digital time-lapse camera stations are multifunctional, provide near continuous data acquisition, are relatively intuitive and efficient, and the increasing availability of high resolution

consumer grade technology stream-lines access to replacement components. However, camera stations aren't alternates to instruments such as discharge stations, but rather fulfill a data gap by supplementing scales of monitoring.

With the spatial infrequency of most water-monitoring, such as stream gauging stations, stochastic occurrences may be challenging to differentiate between malfunctions in sensors, outliers, or other irregularities. Where preexisting infrastructure is lacking, the application of time-lapse imagery provides efficient high frequency documentation to supplement monitoring initiatives and validate anomalies in measurement data. This was demonstrated at DRW during June 2014, where an irregularity in passive measurements was observed as an abrupt decrease in dissolved oxygen (Figure 18). Time-lapse imagery substantiated the abrupt change in water chemistry, as it captured a rapid surge in water inundation within a short time period.

Historically, the Platte River Basin's natural flow regime was broadly characterized by responses to predictable environmental occurrences such as flood-pulse events from snow-melt in the spring. As streamflow is a deterministic factor in river systems, changes in the hydrology can have significant impacts on the rates of chemical reactions, metabolic activity in aquatic organisms, and the solubility of dissolved oxygen (Sinokrat & Gulliver 2000). During 2013 and 2014, visual analysis of the hydrograph at PCC and RRC reflected temporal fluctuations associated with anthropogenic alterations and an engineered hydrograph (Figure 6). A moderate peak in streamflow was observed at both locations, but demonstrated fluctuations at fixed intervals in response to engineered water releases intended to maintain sufficient flows for wildlife during the spring.

At all three study locations, PCC, RRC, and DRW, surface water fluctuated with seasonality. As expected, this was exhibited as increased water temperature during the summer months (Figure 7). A significant factor in river systems, the temporal variability of water temperature was found to be an important variable during the study period as water quality parameters fluctuated as a response to known associations with temperature, including seasonal trends and diel variation of dissolved oxygen concentrations. In addition, water temperature was found to be associated with similar and disparate factors at DRW and RRC. At DRW, water temperature was highly related to water inundation, a response that can be attributed to rising water levels increasing the water column depth and decreasing the reach of solar radiation given the entirety of the wetland. Contrary to previous findings, water temperature in the river was not associated with streamflow during the study period (Dinan 1992, Zander 1996, Sinokrot 1996). The data suggests the dominant influence on mean daily water temperature in the river was seasonality, observed as an association with Julian day.

The Platte River reached a maximum temperature of 31° C during the study period. This level falls just below Nebraska's General Criteria for Aquatic Life maximum limit, recommended at 32° C for warm water systems (NE DEQ 2012). The biological structure, toxicity to contaminants, and metabolic rate of organisms in freshwater are governed by water temperature, and elevated temperatures are stressful for aquatic life. Thermal regimes are a deterministic factor in freshwater systems, impacting gas solubility, atmospheric exchange rates, and other chemical processes (Theurer et al. 1984). Solubility in freshwater systems is a function of water temperature where colder temperatures increase solubility and therefore, as expected, water temperature was inversely related to dissolved oxygen levels, and exhibited seasonal

trends of increased levels in colder seasons and decreased concentrations in warm periods. Increased water temperatures can have significant implications on the organismal life in the river, where elevated temperatures in the central Platte River have resulted in fish die-offs (Dinan 1992).

Streamflow in the river and inundation of the wetland exhibited differences in temporal fluctuations. Water levels in the wetland were highest during the spring season and gradually decreased, a trend similar to the historic hydrograph of the Platte and likely a result of melting snowpack from the surrounding landscape. Water inundation at the wetland did not show as much stochastic variability compared to the river channels (Figure 6), a function that may be attributed to systematic differences in morphology and hydrology. At DRW, increased water levels were associated with increased amounts of nitrate, DEA, and pH and decreases in turbidity and atrazine. Increased streamflow in the river channel at RRC was associated with elevated levels of ammonia and atrazine. These findings may be indicative of differences in the aquatic systems themselves, possibly attributed to the dissimilarities in physical structure and processes; water level increases in the wetland may result in less sediment mixing in the water column, and thus, less turbidity and less atrazine which is known to bond to particulates (World Health Organization 1990).Alternatively, or in addition to inherent structural differences, these findings may be suggestive of dissimilarities in the contaminant load related to underlying groundwater, reflecting a difference in local to regional land use or other anthropogenic influences. In addition, water inundation at DRW was associated with decreases in water temperature, which may influence solubility and uptake of nutrients and account for system discrepancies. Broadly, the results may suggest that surface water in the Platte is influenced by run-off from surrounding

land-use practices, but at greater spatial extents than the study area, as observed precipitation was not a significant contributor to water quality variability. This could be attributed to limited rainfall, water-use, absorbent sediment in the surrounding basin, the spatial limitation of weather data, or the spatial extent of flow and natural braided characteristics of the Platte River Basin.

Overall, observed water quality was within the recommended limits during the study period. A primary indicator of water quality and essential for aquatic life, dissolved oxygen in Nebraska has a criterion for aquatic life of a one-day minimum of not less than 5.0 mg/l and a seven-day mean of not less than 6.0 mg/L from April 1 through September 30 (NE DEQ 2012). During the study period, dissolved oxygen levels remained above 5.5 mg/L in the river channels, but reached concentrations below 2 mg/L in the restored wetland during June and August of 2014. Channel catfish, an abundant species in the Big Bend Reach, can survive at levels of 5 mg/L of dissolved oxygen but ideal levels are around 7 mg/L. Growth and feeding is limited at levels below 3 mg/L (Sidle 1989). Nitrate concentrations at both sites were often below 1 mg/L, similar to the findings of Snow & Spalding 1988. The observed pH measurements during the study period remained within the US Environmental Protection Agency's recommendation of 6.5 to 9.0 (USEPA 2010).

Multivariate Time-series Analysis

Temporal and spatial fluctuations of freshwater systems are determined by interacting intrinsic and extrinsic drivers (Angeler 2011). Rivers and wetlands are linked in a complex dynamical freshwater system; driven by similar processes, nested within a landscape, and hydrologically connected, but differ in structural and functional characteristics, including physical attributes (i.e. water quantity, depth), and biotic communities (Kusler 1992, Coe 1998, Mitsch & Gosselink 2000). The significant temporal fluctuation patterns of surface water

dynamics were quantitatively determined using multivariate time-series modeling. The analysis was able to discern distinct and comparative temporal patterns during the study period and the parameters contributing to the fluctuation patterns within the aquatic systems of the Central Platte River Basin, Nebraska.

Multivariate time series modelling identified temporal patterns in the wetland, DRW that exhibited fluctuations at marginally faster temporal intervals than the river system, RRC, (Figure 16 & Figure 17). This was demonstrated by the significant AEM eigenfunctions comprising the constructed patterns at DRW, which included AEMs 1,2,3,6,12,13, and RRC, comprised of AEMs 1,2,3,7,5,10,4,9. Lower ranking AEMs (i.e. V1) are representative of broad, long term time-scales, while higher values (i.e. V13) denote shorter intervals of oscillation. The difference in fluctuation rates between aquatic systems may be attributed to multiple factors. The higher volume of water contained within the river system compared to the wetland may impact the extent to which hydrogeochemical changes to various inputs affect the water quality dynamics of the entire system. Frequency differences between sites may also result from intrinsic drivers, unique to each aquatic ecosystem.

The extrinsic factors that govern water quality dynamics in the Central Platte River basin is conveyed by the similarities of temporal fluctuations between the first RDA at RRC and DRW. The water quality variables contributing to the patterns (ammonia, turbidity, DEA, total organic carbon, and at DRW – water inundation) provide further explanation. The seasonal directionality associated with the first RDA at both sites, with decreasing linear combination scores (LC) in the spring and increasing LC scores during the fall, is indicative of water quality dynamics driven by external influences operating at similar temporal scales within each aquatic

system, such as weather events and temperature. Landscape and land-use are substantial factors affecting water quality in watersheds (Frenzel et al. 1998). Excess rainfall transported through an agriculturally-dominant landscape, such as the Central Platte River Basin, carries soil, nutrients, pesticides, and other organic material to surface water (Dickey et al. 1982). Agricultural runoff, and the resulting erosion of sediment, can increase concentrations of ammonia, DEA, total organic carbon, and turbidity in aquatic ecosystems (Chapman & Kimstach 1996). The extent which agricultural runoff influences the water quality parameters comprising the first RDA at both study locations may be interrelated with additional extraneous variables. Streamflow, decaying organic material, climate, weather, seasonality and the interactions among these components, may play an integral role in shaping the first RDA identified within both systems by way of increased transport capacity in water, erosion, soil characteristics, and imports of allochthonous material (Schlesinger & Melack 1981, Chapman & Kimstach 1996). Interestingly, in the river channel streamflow was not a significantly contributing factor to RDA 1. This may be attributed to liquid dilution, as higher quantities of water dilution may have increased concentrations, and therefore, we did not observe a correlation with increased levels of the contributing water quality variables. Previous studies have found similar results; Schlesinger & Melack (1981) discuss the influence of streamflow on concentrations of ammonia, but note that most published data only find a weak correlation.

The significant characteristics and marginal differences of the second RDA at both sites exhibits the interplay of inherent and external factors. The temporal patterns broadly mirror each other, as the second RDA at DRW is loosely an inverse of the second RDA at RRC, but with observable differences. The patterns suggest the extrinsic forces may be setting the stage for

intrinsic influences, resulting from the interaction of large scale influences with localized systematic differences. This is reinforced by the deterministic water quality variables demonstrating similar associations, although directionally opposite. The river exhibited more temporal patterns compared to the wetland, which may suggest greater, or a difference in complexity in the riverine system attributed to water dynamics functioning at a larger, more connected, spatial extent with more various inputs in the compared to the wetland. The third RDA identified at both sites captured distinctly dissimilar temporal fluctuations, which suggests the fluctuations and associated water quality parameters may be influenced by internal mechanisms of each aquatic system, such as the direct riparian area or adjacent landscape. The similarities, differences, fluctuation patterns, and the associated relative importance of water quality variables offers a unique insight and discerning characterization of watershed functioning.

The central Platte River Basin exhibited water quality fluctuations driven by extrinsic and intrinsic factors varying over time. Coupling water quality sampling with data derived from time-lapse imagery has the potential to enhance the monitoring of complex system changes and identify fluctuations. Understanding the temporal variability within river systems is an imperative step in the sustainability, management, and conservation of limited water resources.

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Tables and Figures

Table 1: Variables, unit of measurement, acquisition method, and abbreviations used to assess temporal fluctuations of surface water in the central Platte River Basin, Nebraska.

Variable	Unit	Method	Abbreviation
Streamflow (RRC, PCC)	cubic ft. /sec (CFS)	USGS	WI
Inundation (DRW)	% water classified	image analysis	WI
Precipitation	inches	24hr accumulation	PRCP
Temperature	celsius	NOAA	TMP
pH	unitless	passive sensor	PHOS
Specific Conductivity	µS/m	passive sensor	SpC
Dissolved Oxygen	mg/L	passive sensor	DO
Nitrate	mg/L	grab sample	NITR
Ammonia	mg/L	grab sample	AMM
Turbidity	NTU	grab sample	TURB
Atrazine	ng/mL	grab sample	ATRZ
Deethylatrazine	ng/mL	grab sample	DEA
Total Organic Carbon	ppm	grab sample	TOC
Total Kjeldahl Nitrogen	mg/L	grab sample	TKN
Total Phosphorus	mg/L	grab sample	PHOS
Orthophosphate	mg/L	grab sample	ORTHO

Figure 1. Plum Creek Complex (PCC), Rowe River Channel (RRC), and Derr Restoration Wetland (DRW) research locations in the Central Platte River Basin of Nebraska

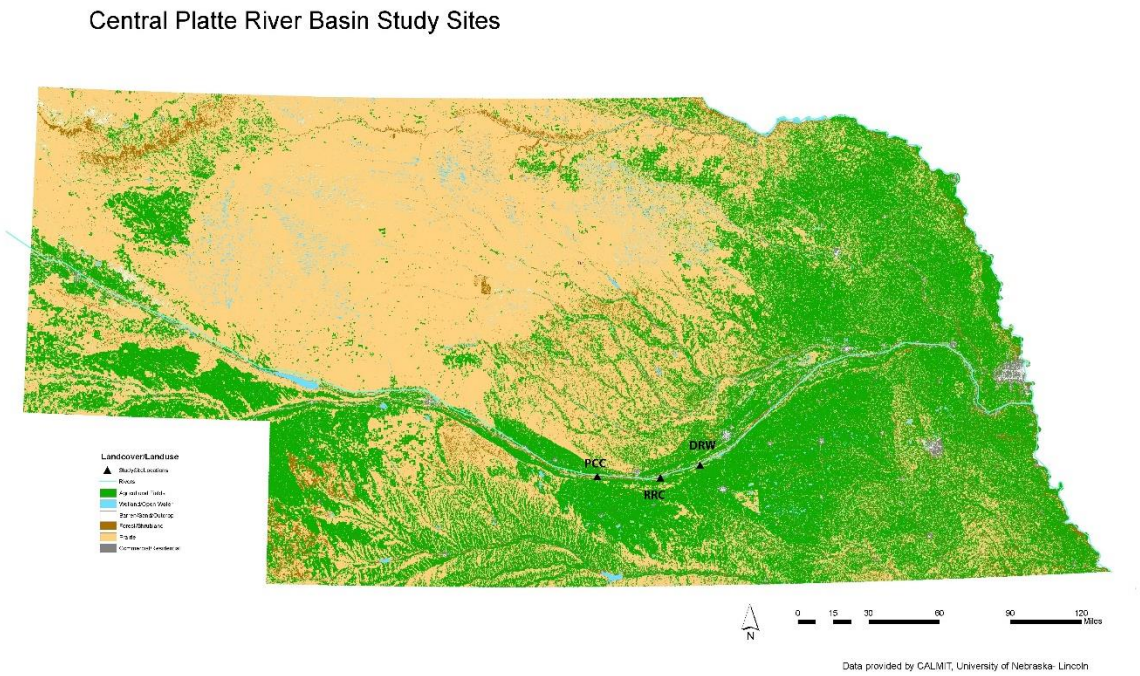


Figure 2. Time-lapse camera system with solar panel owned by Platte Basin Timelapse in the central Platte River Basin

Figure 3. Passive monitoring of surface water in the central Platte River Basin

Figure 4. Classification of water inundation at Derr Restoration wetland from time-lapse imagery analysis using ImageJ and a custom script in HSV space.

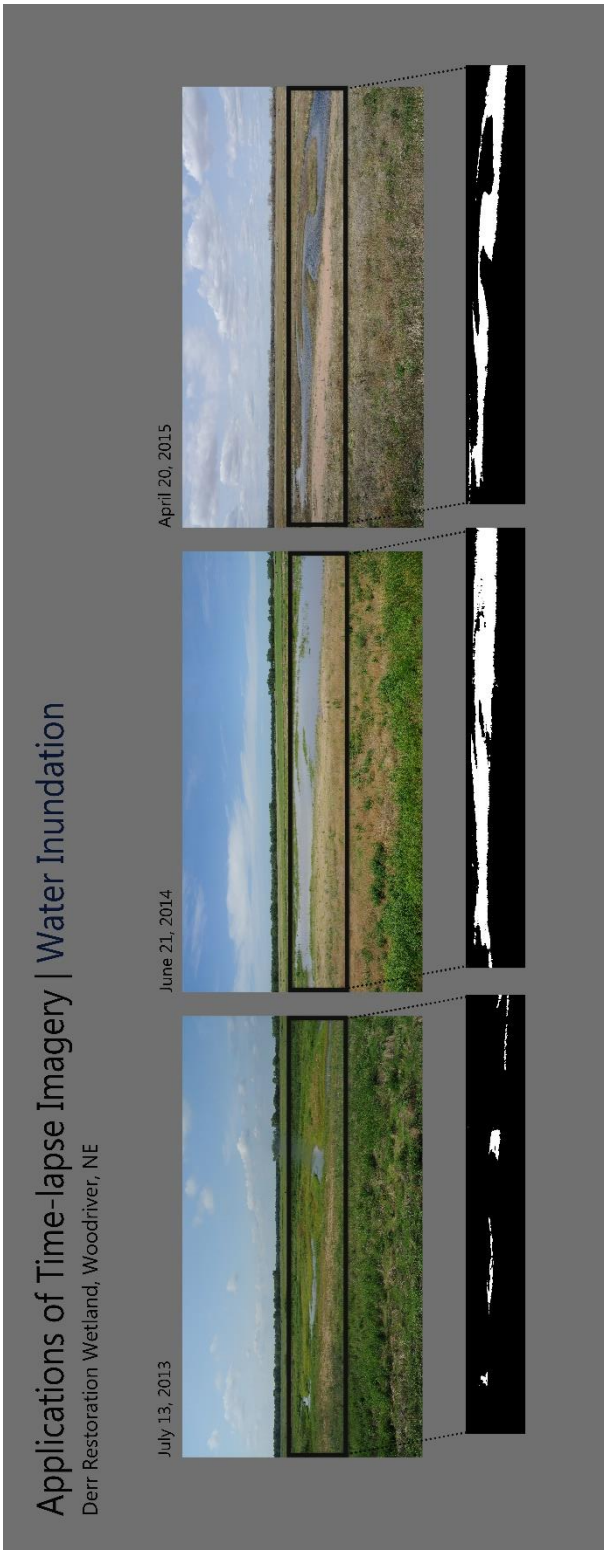


Table 2. Summary statistics for environmental, passive, and active data measurements at Derr Restoration Wetland (DRW), Rowe River Channel (RRC), and Plum Creek Complex (PCC), during 2013 and 2014 in the central Platte River Basin, Nebraska.

	Derr Restoration Wetland				Rowe River Channel				Plum Creek Complex			
Variable	*Min.*	*Max.*	*Mean*	*SD*	*Min.*	*Max.*	*Mean*	*SD*	*Min.*	*Max.*	*Mean*	*SD*
Environmental												
Streamflow/ Inundation	0	15	7	5	2	6610	811	1099	12	12444	1200	1934
Precipitation	0	1.87	0.05	0.2	0	2.52	0.09	0.3	0	1.5	0.11	0.27
Passive												
Temperature	4.3	30.7	18.7	6.8	1.6	28.8	18.7	6.9	2.2	31.4	18.5	6.9
pH	7.4	8.75	8.15	0.3	7.36	8.97	8.36	0.29	7.65	9.16	8.44	0.32
SpConductivity	572	1143	1029	87	250	1117	820	187	549	1207	878	132
Dissolved Oxygen	1.19	12.9	8.53	2.4	5.63	12.93	8.67	1.45	5.53	12.93	8.81	1.6
Active												
Nitrate	0.018	2.05	0.3	0.5	0.016	2.33	0.74	0.64				
Ammonia	0	0.55	0.14	0.1	0	0.32	0.08	0.08				
Turbidity	0.1	70	8.6	0.1	0.1	82	13.01	20.53				
Atrazine	0.12	0.76	0.25	0.1	0	0.29	0.08	0.06				
DEA	0.13	0.44	0.26	0.1	0.06	0.14	0.08	0.02				
TOC	0.91	7.46	4.42	1.9	0.07	6.29	2.88	1.71				
TKN	0	4.44	1.25	0.8	0.35	4.21	1.57	1.01				
Phosphorus	0.01	0.34	0.08	0.1	0.02	0.36	0.13	0.08				
Orthophosphate	0	0.28	0.03	0.1	0.01	0.12	0.04	0.02				

Figure 5. Illustrative example of AEM eigenvalues used in multivariate time series analysis. V1 corresponds to linear trends and subsequent variables increase from slow to rapid frequencies.

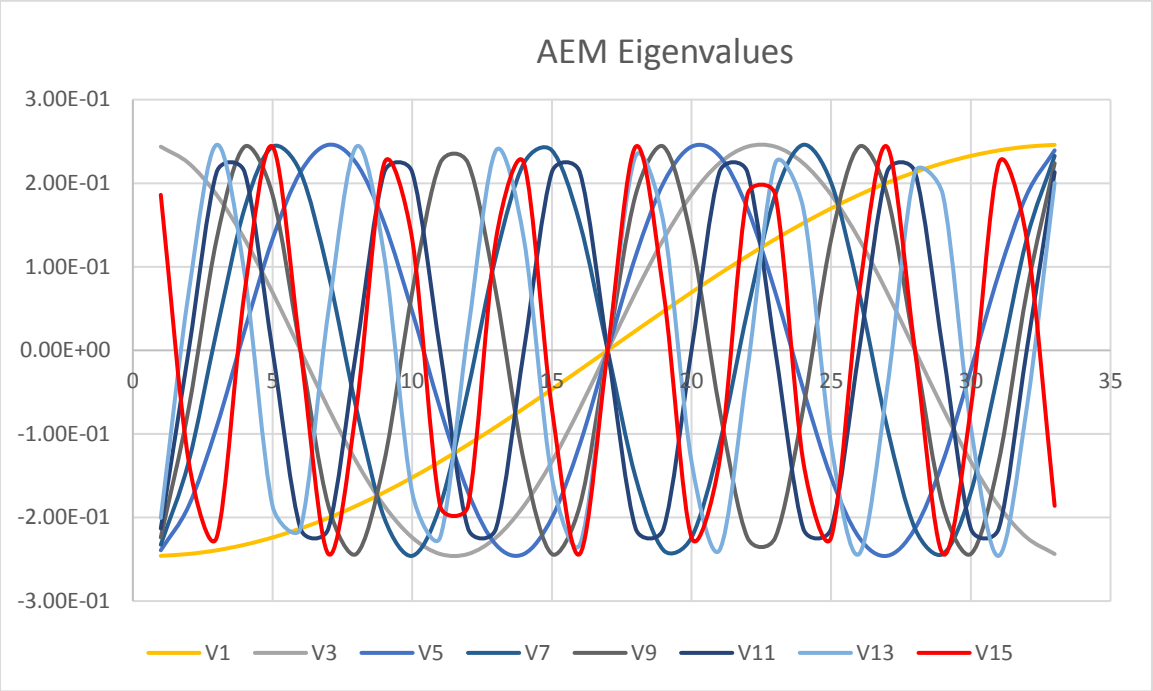


Figure 6. Passive water quality trends in 2014 at Derr Restoration Wetland (DRW), Rowe River Channel (RRC), and Plum Creek Complex (PCC) in the central Platte River Basin, Nebraska. Note: * WI data have been scaled

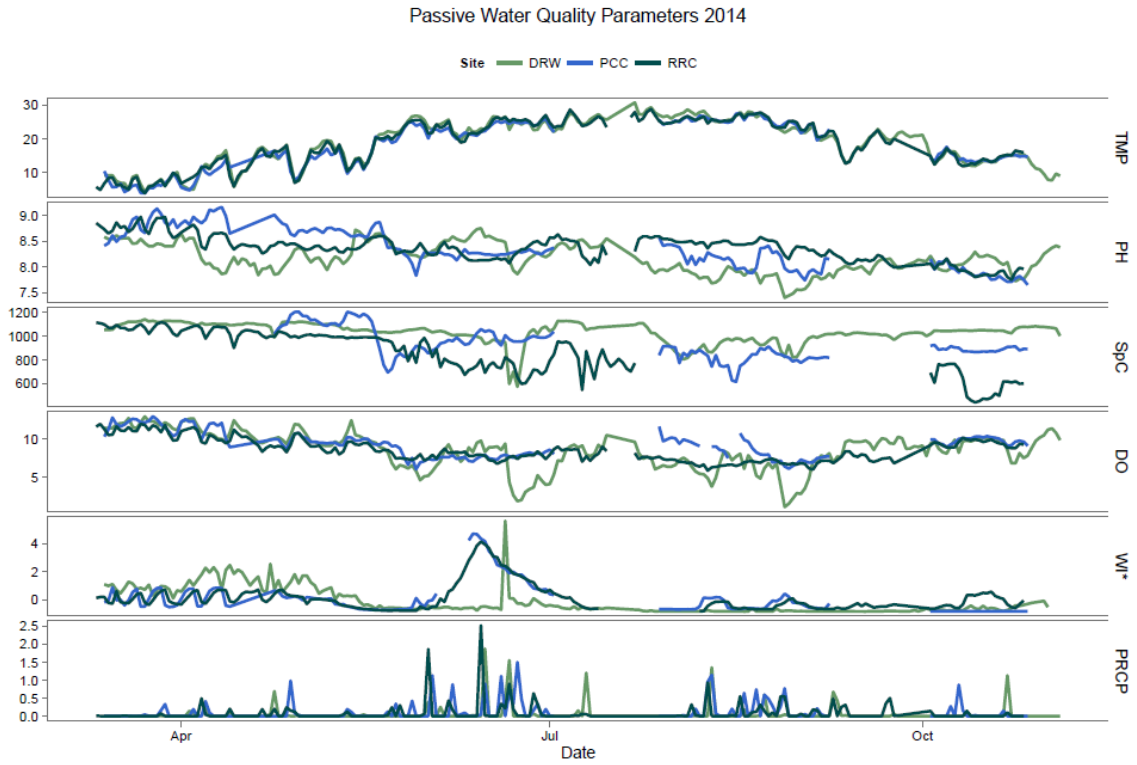


Figure 7. Boxplot of monthly averaged passive water quality measurements.

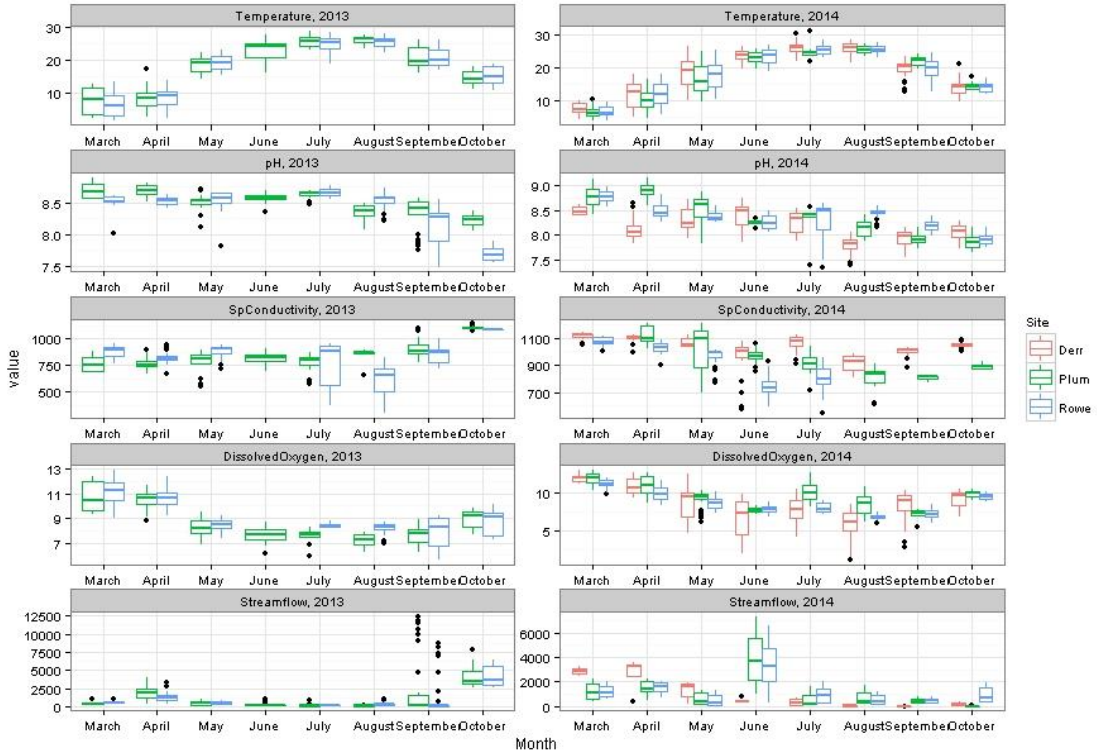


Figure 8. Spearman's Rank Correlations of passive water quality parameters at Plum Creek Complex (PCC), during 2013 and 2014 in the central Platte River Basin, Nebraska. Note: Significance of p-value denoted as *** = <0.01, ** <0.05, * <0.10

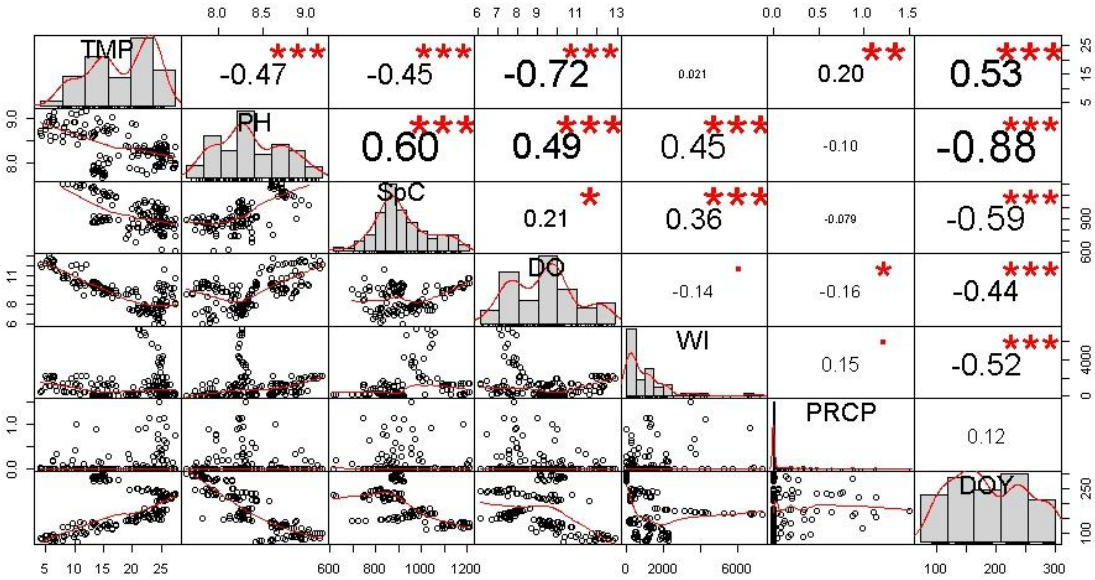


Figure 9. Spearman's Rank Correlations of passive water quality parameters at Rowe River Channel (RRC), during 2013 and 2014 in the central Platte River Basin, Nebraska. Note: Significance of p-value denoted as *** = <0.01, ** <0.05, * <0.10

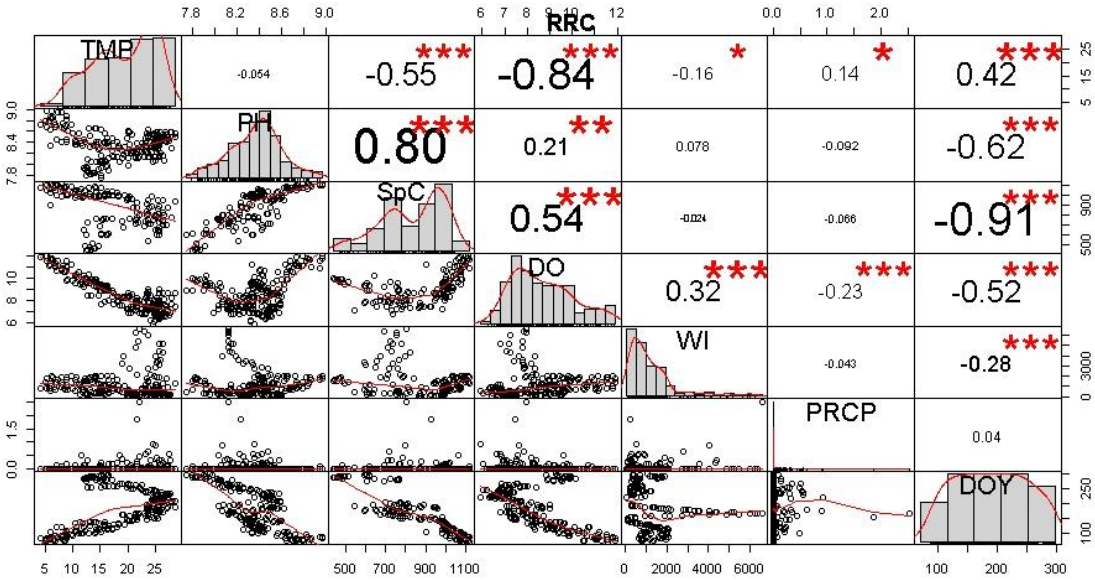


Figure 10. Spearman's Rank Correlations of passive water quality parameters at Derr Restoration Wetland (DRW), during 2013 and 2014 in the central Platte River Basin, Nebraska. Note: Significance of p-value denoted as *** = <0.01, ** <0.05, * <0.10

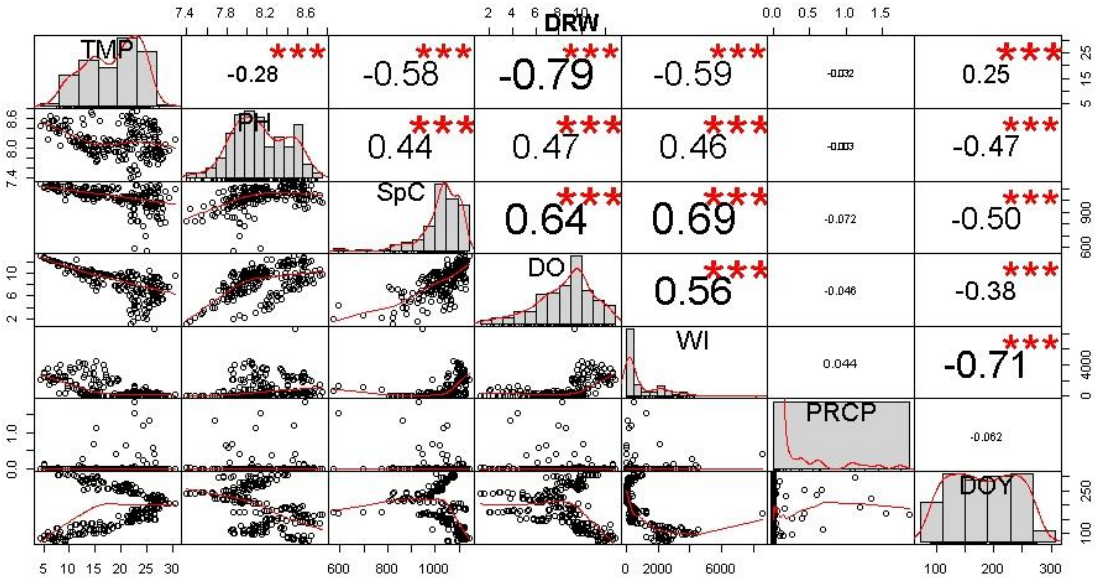


Figure 11. Active water quality trends in 2014 at Derr Restoration Wetland (DRW) and Rowe River Channel (RRC) in the central Platte River Basin, Nebraska. Note: *WI data have been scaled

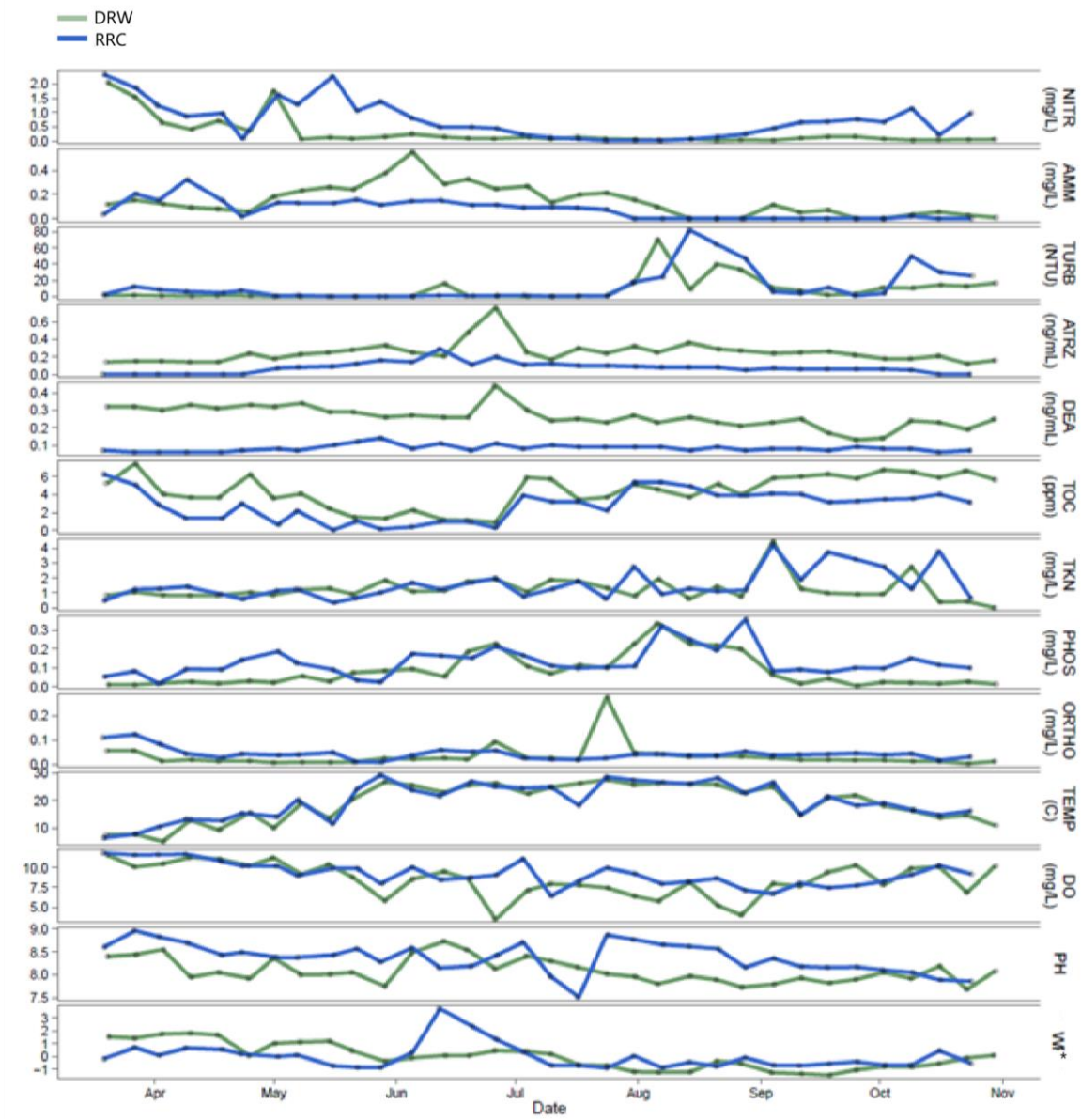


Figure 12. Correlation analysis results of active water quality samples at Derr Restoration Wetland in 2014.

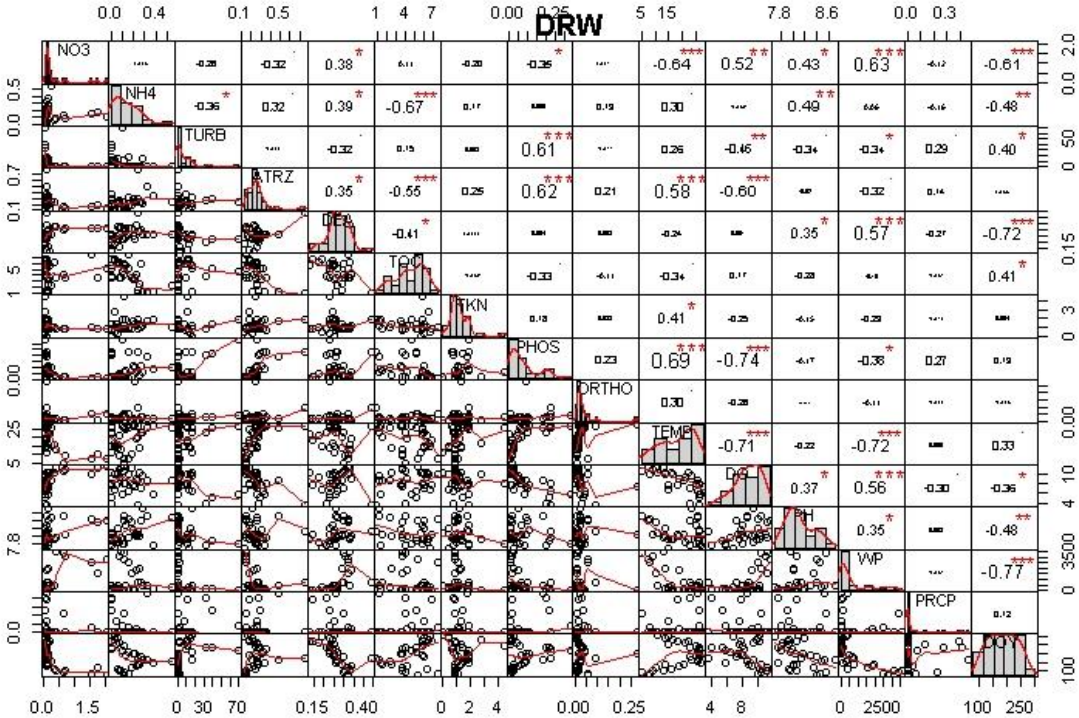


Figure 13. Correlation analysis results of active water quality samples Rowe River Channel in 2014.

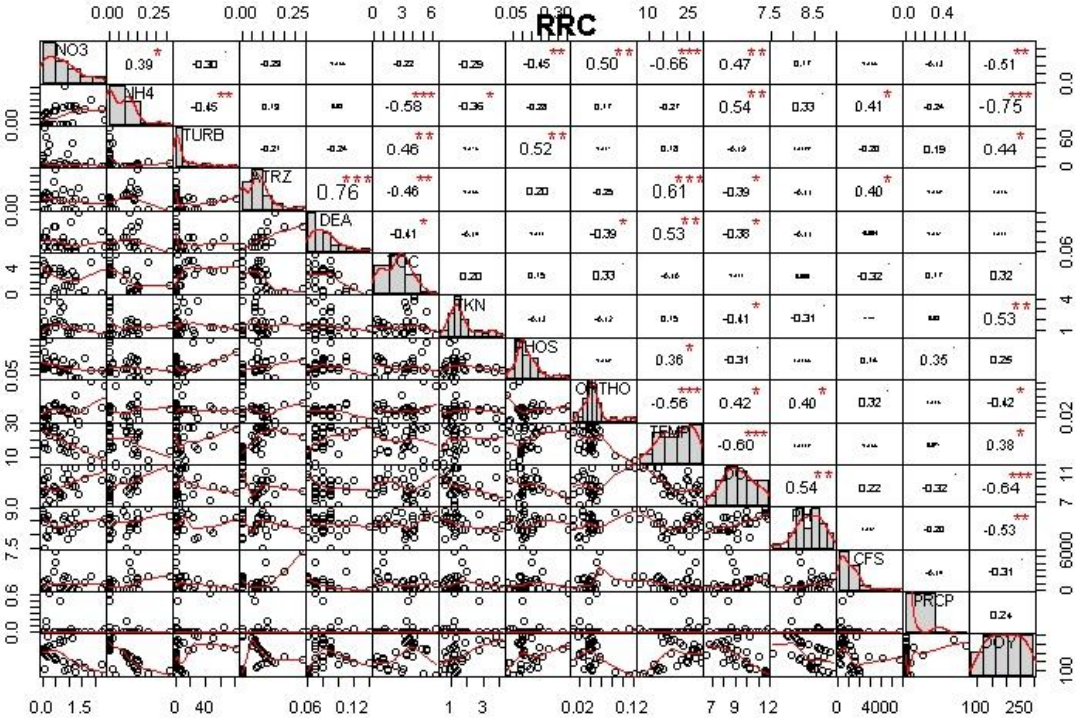


Figure 14. Boxplots of monthly active water quality parameters at DRW and RRC during 2013 and 2013 in the central Platte River Basin, Nebraska.

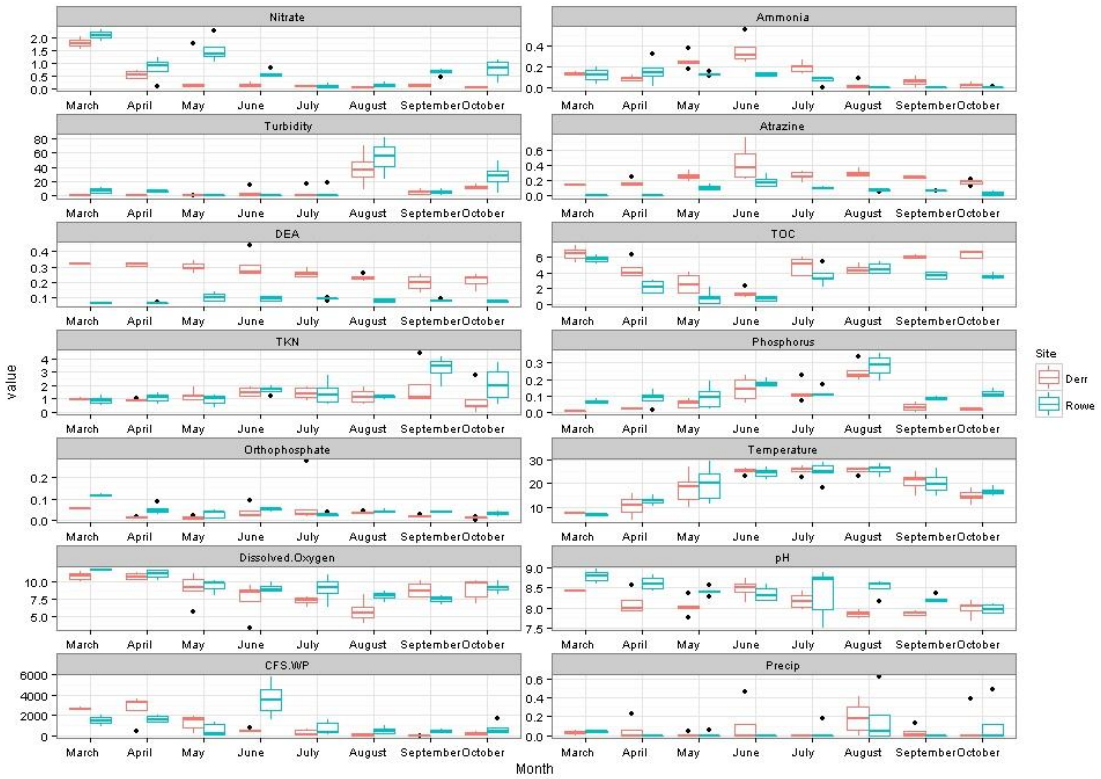


Figure 15. Boxplots of active water quality measurements during entire study period in 2014.

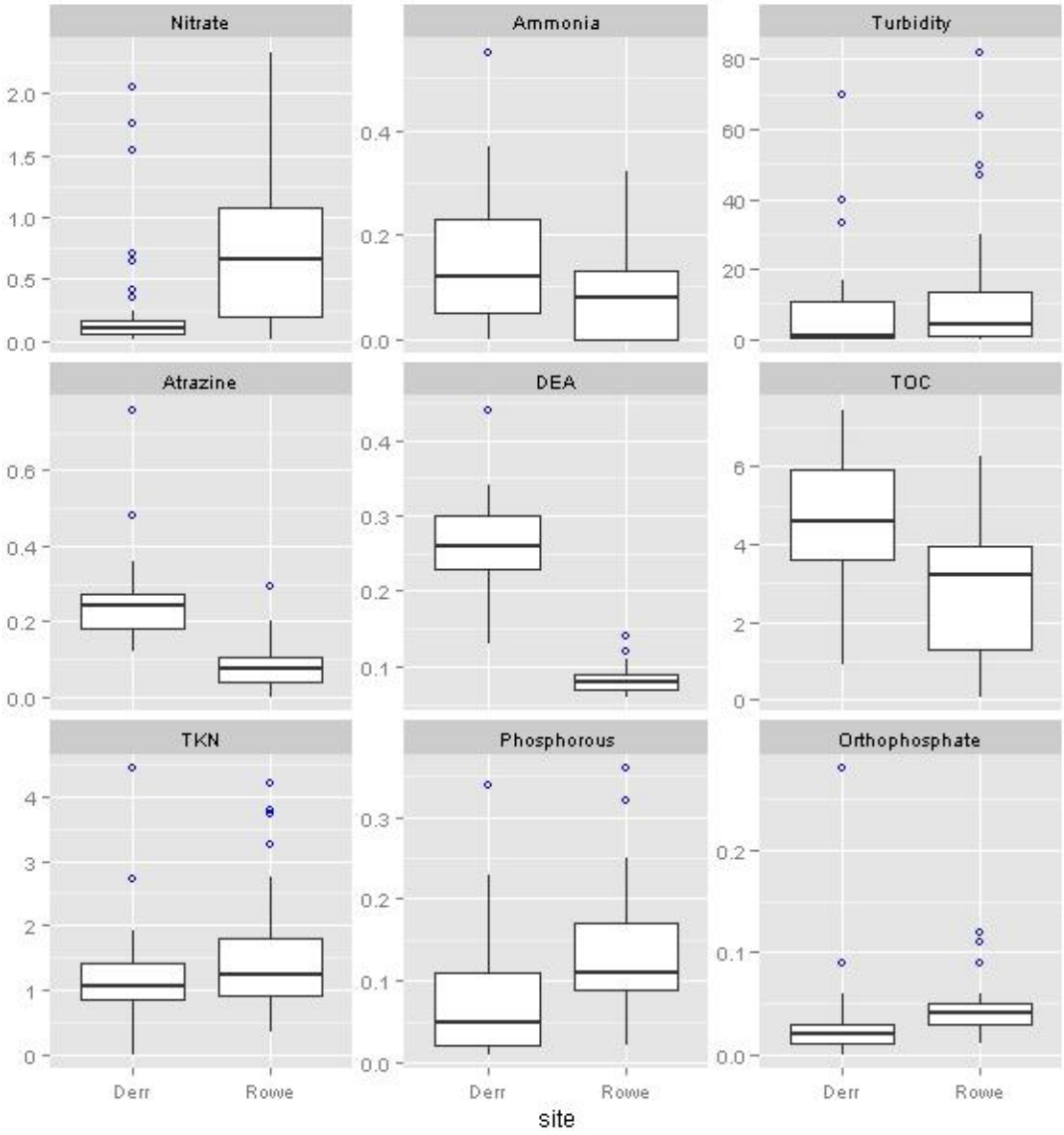
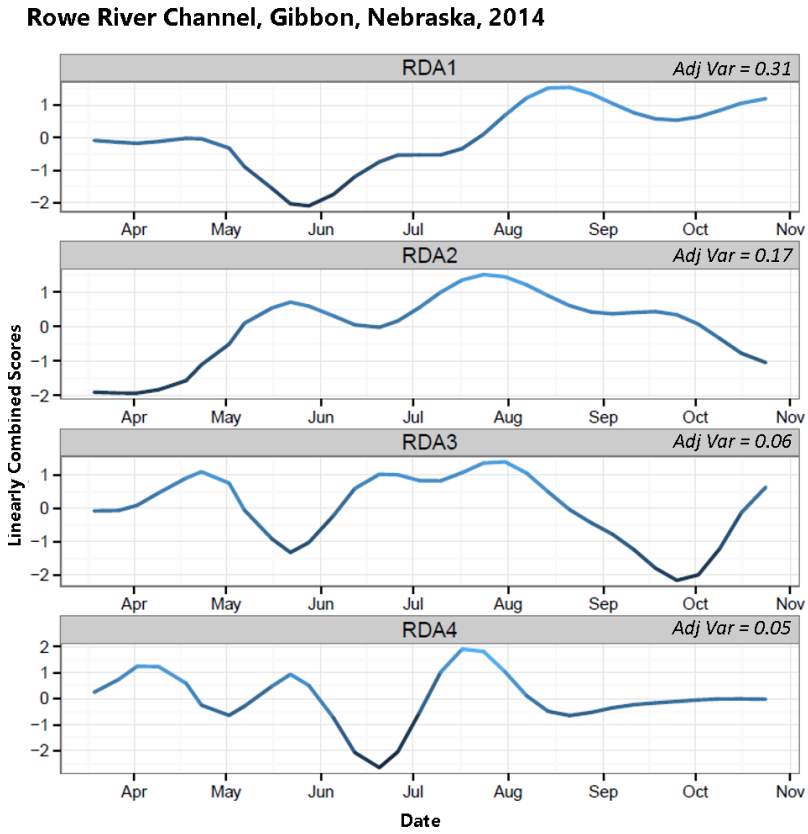


Figure 16. LC score plot illustrating the temporal patterns of water quality fluctuations, associated adjusted variances, and Spearman's correlation of contributing parameters at RRC during 2014.



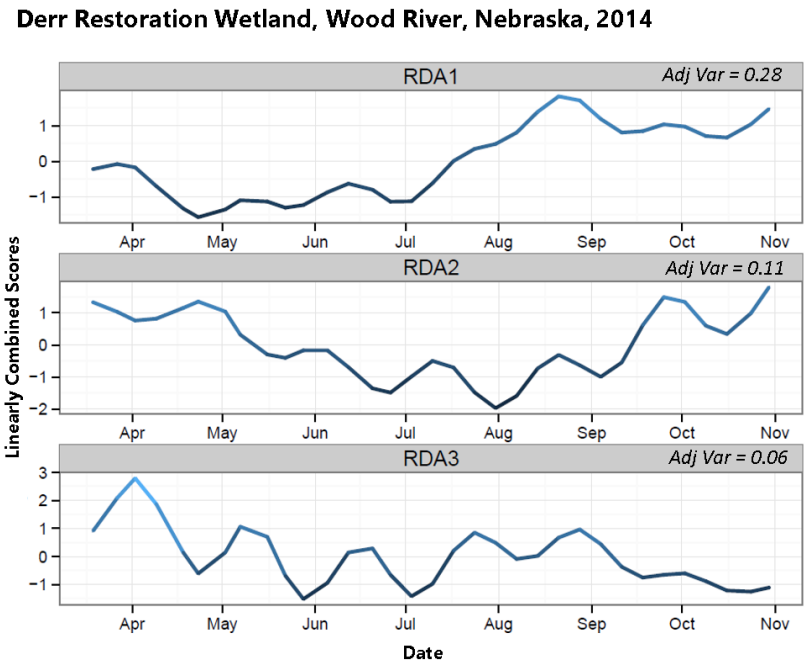
Variable	r	p-value
TOC	0.72	<.01
Turbidity	0.68	<.01
Ammonia	-0.67	<.01
DEA	-0.51	<.01
Atrazine	-0.49	<.01

Variable	r	p-value
Temperature	0.79	<.01
DO	-0.67	<.01
Atrazine	0.59	<.01
DEA	0.58	<.01
Ortho	-0.58	<.01
Nitrate	-0.54	<.01

Variable	r	p-value
TKN	-0.39	.03
Nitrate	-0.36	.04
CFS	0.36	.05

Variable	r	p-value
CFS	-0.61	<.01
Phosphorus	-0.46	.01
Atrazine	-0.43	.01

Figure 17. LC score plot illustrating the temporal patterns of water quality fluctuations, associated adjusted variances, and Spearman's correlation of contributing parameters at DRW during 2014.

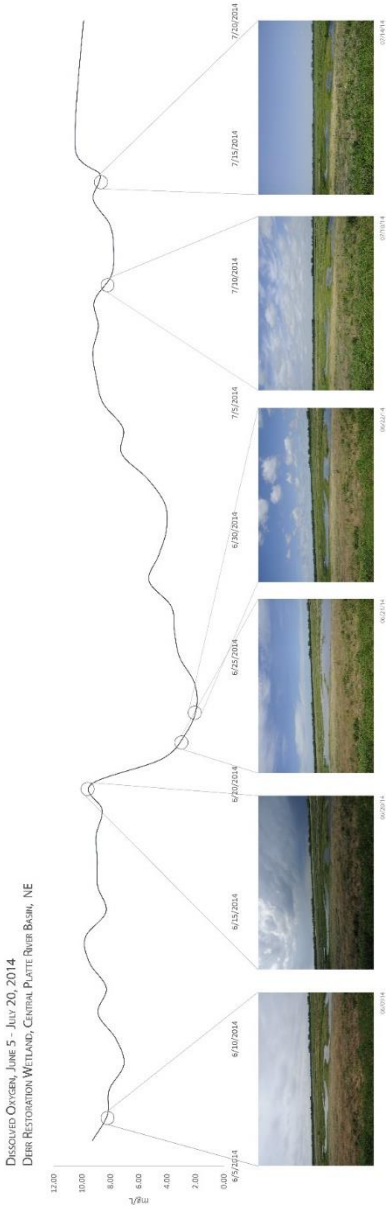


Variable	r	p-value
DEA	-0.68	<.01
Ammonia	-0.67	<.01
Inundation	-0.63	<.01
Turbidity	0.57	<.01
TOC	0.52	<.01

Variable	r	p-value
Phosphorous	-0.76	<.01
Temperature	-0.75	<.01
DO	0.66	<.01
Atrazine	-0.60	<.01
Nitrate	0.45	.01
TKN	-0.42	.02

Variable	r	p-value
Inundation	0.48	<.01
Nitrate	0.40	.02

Figure 18. Irregularity in time-series data at DRW clarified by time-lapse imagery.



CHAPTER 4. ECOLOGICAL FACTORS ASSOCIATED WITH SEASONAL BAT ACTIVITY IN THE CENTRAL PLATTE RIVER BASIN, NE

Introduction

Interactions between wildlife and their environment are synchronously intertwined. However, shifts in the timing of ecological events have been observed; a result of a globally changing climate that threatens to desynchronize the temporal dynamics of ecosystems (Middleton et al 2013, Johanson et al. 2015). Understanding phenology, the timing of seasonal biotic occurrences and their relationship to environmental factors (Lieth 1974), is essential to mitigate the impacts of climate change and effectively manage animals and their habitat. In seasonally variable environments, such as the Great Plains of Nebraska, hibernation and migration are common phenological strategies for wildlife to survive periods of inadequate resource availability and unfavorable climatic conditions. These phenological occurrences are demonstrated by resident and migratory bat species. In recent years, management of bat populations and their habitats across the United States has received increased attention as a result of drastic population declines. Aggregated impacts of commercial wind turbine facilities (Cryan et al. 2014), land-use changes, water scarcity, environmental contaminants, global climate change, and white-nose syndrome (WNS), a fatal fungal disease, make understanding the interactions and temporal dynamics of bats and their environment a pressing challenge (Weller et al. 2009, Jones & Rebelo 2013).

Bats are sensitive to environmental and climatic changes (Jones et al 2009), attributed partially to their longevity, low fecundity, and high survivorship (Wickramasinghe et al. 2004). Thus, bats play a key role as bioindicators, capable of reflecting ecological variation, and the

temporal dynamics of bat activity in relation to biotic and abiotic factors may be telling of larger scale changes within ecosystems. However, a baseline understanding of the phenological dynamics of bats and their environment is needed to differentiate directional change from random variation. The influence of temperature, wind speed, precipitation, and other environmental variables on bat activity have been documented in the literature (Parsons et al. 2003, Arnett et al. 2006, Baerwald & Barclay 2011), although some discrepancy remains regarding the effects of some variables such as moon and barometric pressure (Ciechanowski et al. 2007). Additional research has demonstrated that bat activity is affected by forest type (Ford et al. 2005) and vegetation density (Loeb and O'Keefe 2006). Hayes (2015) and Cryan (2014) have shown the spatial influence of environmental factors, including vegetation, by mapping species distributions (Hayes et al. 2015, Cryan et al. 2014). However, limited research has examined the temporal relationship between vegetation dynamics and seasonal bat activity. Due to their small body size, nocturnal activity, and historically negative perception within society, bats can be challenging to study. Examining the phenological phase of vegetation may provide guidance and offer additional insight into these elusive mammals.

Vegetation dynamics are indicative of primary productivity, energy availability (Jetz et al. 2009, Yang et al. 2010, Toomey 2015, Weigand 2008), and are influential in the distribution, life history traits, and temporal occurrence of wildlife (Pettorelli et al. 2011, Wiegard 2008, Evans et al. 2008, St-Louis et al. 2009). Temporal changes in vegetation have shown to correlate with the activity of numerous species including birds (La Sorte et al. 2014, Klaasen et al. 2010, Shariatinajafabadi et al. 2014), elk (Middleton et al. 2013), and additional wildlife movement (Inouye et al 2000). For insectivorous bats, vegetation phenophase may be a cue for food

availability, as changes in vegetation are an indication of insect availability (Wickramashinghe et al. 2004, Fukui et al. 2006, Britch et al. 2008, Bater 2011, Hagen 2014). It may further signal adequate resource availability in the form of structural complexity for protection, or roosting and foraging habitat (Rydell et al. 1996). Structural complexity of vegetation may be of particular importance for foliage-roosting bat species, such as Lasiurines, which rely on adequate leaf cover for shelter, and a suitable roosting environment may be a restrictive factor for habitat (O'Shea et al. 2003). Given the threats present to bats, and limited scope of phenological knowledge in Nebraska, I sought to further the understanding of bat activity in an agriculturally dominant and ecologically significant region of the Great Plains of Nebraska. Specifically, I focused on three goals.

1. To identify what bat species are present in the study location from echolocation calls.
2. To assess relative activity as a function of time to characterize bat phenology.
3. To examine the relationship between bat activity and ecological factors, such as the widely regarded influence of temperature and wind speed, and the novel inclusion of vegetation phenology.

Methods

Study area

The study region is an approximately 120km section of the central Platte River Basin extending from Lexington, Nebraska, USA, eastward to Grand Island, in south central Nebraska (Figure 1). The area is ecologically critical and provides breeding habitat for birds, a key migratory corridor for thousands of Sandhill cranes and waterfowl, and an essential region for

numerous endangered species including whooping cranes (*Grus Americana*), interior least terns (*Sterna antillarum*), and piping plovers (*Charadrius melodus*)(NRC 2004). Reduced stream flows in the Platte River have allowed vegetation growth on surrounding riparian areas, resulting in an abundance of invasive species and woody encroachment such as Purple loosestrife (*Lythrum salicaria),* Common Reed (*Phragmites*), Eastern Red Cedar (*Juniperus virginiana*), and Russian Olive (*Elaeagnus angustifolia*) (Eschner et al. 1981). In addition, reduction in streamflow variation has increased forested patches in the riparian zone, and potentially expanded the spatial distribution of woodland animals, including bats (Benedict 2000, Geluso et al. 2005).

Study Sites

Three study sites, Plum Creek Complex, Rowe Sanctuary, and Derr Restoration Wetland, are located within the Central Platte River Basin (Figure 2). Plum Creek Complex is situated on the south channel of the Platte River, the furthest west site between the towns of Lexington and Overton, Nebraska. The area is managed for endangered avian species and thus disked to reduce vegetation. The north side of the channel remains forested. Rowe Sanctuary, in Gibbon, Nebraska, is maintained by the National Audubon Society and adjacent to the Platte River's south channel. The site is characterized by riparian wetlands, forested patches, and agricultural fields. Derr Restoration Wetland is located furthest east on a section of The Nature Conservancy's Platte River Prairies tract of land in Wood River, Nebraska. This site consists of a wetland slough with a meandering stream channel that was restored from a sand and gravel mining pit in 2011.

Acoustic Monitoring and Bat Classification

At each study location, passive acoustic surveying was conducted using a full-spectrum ultrasonic detector (SM2BAT+, 192 kHz sampling rate, +48 gain, 2 sec trigger window; Wildlife Acoustics, Inc., Concord, MA) and an ultrasonic microphone (SMX-UT). Each microphone was mounted approximately 3.5m above the ground at a 45° angle and the cone of detection, or a distance of approximately 30 meters for 280° around the detector, was free of obstruction, vegetation, and overall clutter. The detectors recorded continuously from half an hour before sunset until sunrise. At Derr and Plum Creek, the detectors were operated in 2013 and 2014 from March until November and from March to June of 2015. The detector at Rowe was deployed nearly year round from March of 2013 to June of 2015. Due to equipment malfunctions and weather, complete coverage was not maintained during the entire recording time. Seasonal periods were determined as spring (March-June 15) summer (June 15-August) and fall (August-October).

Passive surveying was used to identify bat species present within the study location and the timing of their occurrence and activity. Assessment of bat activity in relation to environmental factors focused on three bat species considered to be most common in the Great Plains (Benedict 2004), resident *Eptesicus fuscus* (Big brown bat), migratory *Lasiurus borealis* (Eastern Red Bat), and *Nycticeius humerali*s (Evening Bat) a presumed regional migrant. Recordings were analyzed using a mixed approach of software and ocular assessment to classify echolocation calls. Files were truncated to 15 seconds and auto classified using Kaleidoscope software (Wildlife Acoustics, Inc., Concord, MA). Recordings identified as noise and sequences with fewer than three pulses and duration of less than two milliseconds (Weller and Baldwin

2012) were discarded due to potential identification error (Britzke 2003). For the purpose of this study, it was therefore defined *a priori* that a bat pass is a sequence of three or more calls and passes were considered a discrete event and treated as independent (Gannon et al. 2003). Passes identified as E. fuscus, L. borealis, and N. humeralis were then visually inspected and manually vetted as accurately as possible using full spectrum in Kaleidoscope and converted zero-cross in Analook for further analysis (Corben 2006).

A relative bat activity index, an inferred natural ratio to relative, not absolute, abundance, was used to examine the relationship between bat activity and environmental factors, as the objective was to assess bat phenology as a discrete proportional change over time and not to make inferences in regards to absolute abundance. Therefore, the relative activity index was defined as the mean number of species-specific bat passes per detector for each night of recording.

Vegetation Dynamics

A high resolution DSLR time-lapse camera was installed at each study location at a height of approximately 3.5 m on a wooden pole in collaboration with the Platte Basin Timelapse project (PBT). Each camera station is comprised of a Nikon D300 DSLR camera with a 12.3 megapixel crop sensor (DX) and Nikkor 18-70mm 1:3.5-4.5 lens. A TRLcam intervalometer (TRLcam.com) controls the interval settings and the timing is adjusted by a GPS module to account for differing daily sunrise and sunset times. The intervelometer was generally set to capture one red-green-blue (RGB) color channel image every hour beginning at sunrise and ending at sunset. The equipment is contained within weatherproof housing constructed from

ultra-violet stabilized polycarbonate plastic made by Serpac with modifications of optical glass, aluminum lens hood, and ball mount to secure the camera to a mounting pole approximately 2.5 meters above ground. The systems are powered by a 30 watt solar panel and stored in a lithium ion battery. Camera operation is verified daily by cellular technology that sends an image via email to confirm acquisition. The images are automatically uploaded to PBT's 1.5 terra-byte image library and accessible through Phocalstream, software technology developed by the Jeffrey S.Raikes School for Computer Science and Management at the University of Nebraska – Lincoln.

Three images a day were selected between the hours of 10:00 and 14:00 for standardization, and images with discrepancies that could alter the analysis (i.e. camera movement, rain drops on lens) were discarded. When possible, discarded images were replaced with new images to complete the three per day sequence. To assess vegetation phenophase, images were batch analyzed by selecting a standard region of interest (ROI) encompassing only vegetation for each site's batch of images. Within the ROI, the average digital number for each Red-Green-Blue (RGB) color channel was used to calculate the Excess Green (ExG) and Green Chromatic Coordinate (Gcc; Equation 1) vegetation indices. The indices were highly correlated, and therefore only Gcc was included in the analysis, as GCC is more robust to variations in weather illumination (Sonnentag 2012).

$G_{CC} = DN_G / DN_R + DN_G + DN_B$ *(Equation 1; Wyszecki and Stiles 1982, Gillespie et al. 1987)*

Climatic / Environmental Variables

Weather data was acquired from the National Climatic Data Center's (NCDC) Climate Data Online database (https://www.ncdc.noaa.gov/cdo-web/) using the nearest NCDC station (<15km) to each research site. Parameters included hourly measurements of temperature, precipitation, barometric pressure and wind speed (Table 1). Nightly (16:00 – 03:00) mean averages of temperature, atmospheric pressure, and wind speed, and the total sum of precipitation, were calculated for each detector night. The change in atmospheric pressure was calculated as the difference in pressure from the previous night's mean ($\Delta Press = meanPress_{x-1} - meanPress_x$). Moon fraction of illumination was acquired from the Astronomical Applications Department of the United States Naval Observatory (AA USNO 2007).

Statistical Analysis

Physiological differences in bat species, seasonal variations in ecological factors, and spatio-temporal changes related to migration, emergence, swarming, or maternity colonies, govern the timing, distribution, and behavior of both resident and migratory bat species. Moreover, ecological factors may differentially influence species. Therefore models were constructed separately for each species (E.fuscus, L.borealis, and N.humeralis). The presence of bat species and activity in summer were examined, however, only spring and fall were included in analysis as the focus was on assessing the relationship of bat activity and ecological factors during time periods of movement (migration/emergence). Predictor variables were chosen *a priori* based on ecological and literature-reviewed justification and inference was made prior to analysis as to the directional influence (Table 1).

All statistical analysis was implemented in R (R development core team 2012). Two methods, Random Forest and Generalized Linear Mixed Models with multi-model inference, were employed to examine the relationship of bat activity and ecological factors during seasonal transition periods (i.e. migration/emergence). This corroboration of analysis utilizing two statistically divergent theoretical methods resulted from the common challenge of accurate bat identification for acoustics and statistical limitations frequent of ecological data.

Random Forest

As climatic, terrestrial, and aquatic systems are inherently complex, analysis of ecological fluctuations and phenomena often challenge the implicit assumptions of traditional statistical methods without a trade-off of losing resolution or data (i.e. reducing daily observations to weekly averages) (Olden et al. 2008). For example, natural processes and cycles are often dependent on time, and thus, violate the assumption of independence. Statistical learning, or machine learning, provides a versatile framework for exploring non-intuitive relationships within ecological data (Evans et al. 2011). Random Forest (RF), a non-parametric method based on an ensemble of Regression Trees (CART) (Breiman et al. 1984, Breiman 2001), has the flexibility to better handle issues commonly associated with ecological data, such as non-normality (Oppel et al. 2009, Strobl et al. 2008). It allows for multiple forms of data (i.e. continuous, categorical, and/or ordinal), does not assume independence and thus may be less affected by autocorrelation (Evans et al. 2011), characterizes complex variable interactions, and has demonstrated highly accurate prediction and model fit compared to more traditional methods (Cutler et al. 2007**,** Olden et al. 2008). Furthermore, RF reduces overfitting, a common drawback of statistical learning, by implementing two elements of randomization; 1) sequential CART

trees do not depend on preceding trees and are built independently through bagging, or constructing bootstrap samples of random subsets of data, and 2) within a tree each node is best split by a random subset of predictor variables (Breiman 2001).

RF models were fit using the package randomForestSRC (Ishwaran & Kogalur 2014). Variable importance (VIMP) was calculated for each predictor variable and ranked by importance. VIMP was constructed using the option 'permute' determined from the prediction error calculated for each variable from out-of-bag (OOB) permutation (MSE for regression), differenced, averaged, and normalized over all trees (Breiman 2001). Partial dependence plots were constructed to show the effect of a variable given all other terms are held constant. Compared to parametric methods, partial dependence plots are more capable of illustrating non-linear relationships between predictor and response variables (Ehrlinger 2015). Site and year were included in models to account for temporal and spatial heterogeneity and annual variation among locations. In addition, RF was used to test interactions among predictor variables. However, none were found to be significant.

Negative Binomial Generalized Mixed Models

Negative binomial generalized linear mixed models were fit using the package lme4 (Bates 2014) and multi model inference was employed using the MuMIn package (Barton 2011). Negative binomial models accounted for overdispersion in the data, as the variance divided by the mean was greater than one (Fournier et al. 2012), a common occurrence with count data (Richards 2008). However, negative binomial models were not able to account for serial autocorrelation within time-dependent data. The negative binomial distribution, a subset of

Poisson, is advantageous as it does not assume normality, compensates for overdispersion, and may reduce bias (White and Bennetts 1996, Boyce et al. 2001). Based on ecologically relevant factors, six suites of models were developed *a priori,* parsed by species (E.fuscus, L.borealis, and N.humeralis) and season (spring, fall). Each suite had 15 candidate models, including a null and global model (Table 6). Site was included in all models as a random effect to account for spatial heterogeneity and variation among locations which allowed model intercepts to vary between sites.

All potential models were checked for multi-collinearity using a test of variance inflation factor (VIF) where resulting estimates were retained if less than two (Zuur et al. 2007). Julian date, a proxy for seasonality, is known to affect patterns of wildlife (Visser et al. 2010), but was highly correlated with multiple variables. Thus, Julian date was excluded from analyses and two ecological indicators and proxies of seasonality; Gcc and temperature, were retained. The remaining predictor variables were not significantly correlated. Data was not transformed as transforming count data to normality can increase bias (O'Hara and Kotze 2010), and transformation is unnecessary when employing negative binomial models. However, predictor variables were scaled to account for discrepancies in measurement units.

Models were ranked using Akaike's Information Criterion with bias correction for small sample sizes (AICc; Burnham and Anderson 2002). The top model was selected based on the model weight and ranking. To assess the results of multimodel inference and the fit of the best model, the coefficient of determination R^2 was computed to estimate the proportion of variance explained (r.squaredLR function in MuMIn package; Nakagawa & Schielzeth 2013). If the model set resulted in high uncertainty, with only small variations in fit across multiple models,

full model-averaging was employed on a confidence set of models (Grueber et al. 2011). The confidence set was comprised of models within 10% of the top model's weight (Royall 1997).

Results

Acoustic Summaries

A total of 41,157 bat passes were detected over 673 detector nights at the three research sites between March 2013 and June 2015 (Table 2). For the duration of the study, the mean was 61.2 (+/- 4.3) bat passes per detector night. Bat passes and the mean number of passes per detector night varied with season (Figure 2). During the spring, a mean of 51 passes per detector night were observed. The highest seasonal mean was observed in the summer, at 95.3 passes per detector night. The lowest mean was observed in the fall, with 24.8 bat passes per detector night. Of the total passes recorded, 12,119 were classified as *L. borealis* (29%), 12,237 as E.fuscus (30%) and 8,236 as N.humeralis (20%). These three species were the most common, consistent with the findings of Benedict (2004) (Benedict 2004). The remaining 21% of bat passes were classified as Lasiurus cinereus (Hoary bat), Lasionycteris noctivagans (Silver-haired bat), Perimyotis subflavus (Tricolored bat), myotids, or unidentified.

Day of the year (DOY) of first and last calls were used to assess and compare the phenological timing of activity between the three most commonly recorded species; E.fuscus, L.borealis, and N.humeralis. During the spring seasons, the mean day of first echolocation call for E.fuscus was DOY 87, the mean DOY for L.borealis was 104, and the mean DOY for N. humeralis was 109. During the fall (or occasionally post-fall), the mean last day an echolocation call was recorded was DOY 284 for E.fuscus, DOY 285 for L.borealis, and DOY 254 for

N.humeralis. The latest call recorded for any species during the study period was classified as L.borealis at Rowe Sanctuary on DOY 315 in 2013, and DOY 314 in 2014.

Random Forest Analysis

Species specific models using RF analysis were constructed using 1000 trees from a sample size of 254 for the three spring seasons of 2013-2015 (Table 3). Models were able to explain 25% of the variance in E.fuscus activity, 38% of L.borealis activity, and 40% of N.humeralis activity. During the fall, species specific RF models were built using 1000 trees from 172 detector nights in 2013 and 2014. Models constructed for the fall were able to explain 2% of the variance in E.fuscus activity, 21% of L.borealis activity, and 17% of N.humeralis activity.

During the spring season, the effect of ecological variables on E.fuscus activity, when all other factors were held at their mean, was observed by the partial dependence plots which illustrated high variability among site and year (Figure 7). Included in the models to account for spatio-temporal variation, results indicate site and year were the most important in predicting E.fuscus activity; highest at Derr wetland, then Rowe river channel, then Plum Creek complex and annual variability with highest activity in 2015, than 2014, than 2013 for the spring season. VIMP analysis of the E.fuscus RF model shows that Site and Year were highly important variables, while TMP and GCC were moderately important variables in determining E.fuscus activity during the spring (Figure 4). TMP was found to be the environmental variable of most importance, and positively associated with E.fuscus activity. This is illustrated by the partial dependence plot with an increase in E.fuscus activity around 35°F and a steady increase until 60°F when activity plateaus (Figure 7). VIMP indicates GCC is the next variable of importance, however its influence on E.fuscus activity fluctuates from 0.34 – 0.37 on the vegetation index,

until activity plateaus. For the fall season, the RF model was not able to comprehensibly describe the observed changes in E.fuscus activity, demonstrated by the low variance explained (1.69%, Table 3), however, GCC, year, site, and WS were the most important variables determined by VIMP (Table 5 & Figure 10). In contrast to spring results, fall activity for E.fuscus was highest at Rowe and lowest at Derr, however given the amount of variation (Table 2), the difference was minimal.

For L.borealis activity in the spring, RF indicated GCC was of considerable importance (relative importance >0.9), while TMP was of high importance, SITE was moderately important, CHGPRS, MOON and year of low importance, while WS and PRCP reduced the accuracy in predicting activity (Table 4, Figure 5). Partial dependence plots illustrated support for expected positive associations among L.borealis activity with GCC and TMP (Figure 8). This was observed with GCC as a steep influx in relative L.borealis activity around 0.36 on the vegetation index, and again at 0.38, before plateauing. The influence of TMP on activity was shown to begin around 45°F and increase until approximately 60°F. A biomodal response of L.borealis activity to CHGPRS was observed, as spring results indicate activity was highest when the change of pressure was negative, or the pressure observed on X night was lower than that of X-1. In the fall for L.borealis activity, GCC, year, site, MOON, and TMP were found to be important variables, WS of moderate importance, PRCP of minimal importance, and CHGPRS reduced the ability of the RF model to predict activity (Table 5, Figure 11). Results indicated a positive association with GCC, observed as a peak in activity at 0.42, decreasing to minimal activity at 0.40. L.borealis activity was found to be higher in fall 2013 than 2014, and at Plum compared to Derr or Rowe illustrated by the partial dependence plots (Figure 14). MOON exhibited a non-

linear relationship with L.borealis activity in the fall, as activity peaked and leveled off at approximately 0.4 until 0.7, when it decreased again. L.borealis activity was positively influenced by TMP, where activity was low to variable at temperatures below 60°F, gradually increased from 60°F to 70°F, and increased sharply at approximately 70°F.

In the spring, RF analysis found GCC, site, and TMP to be highly important factors, and MOON, year, and CHGPRS, to be of low importance for explaining N.humeralis activity (Table 4, Figure 6). PRCP was of no importance, but however, did not negatively affect prediction, while WS decreased the accuracy of the RF model. In relation to Gcc, N.humeralis activity exhibited a sharp increase in relation to Gcc at approximately 0.35 and again at approximately 0.39 (Figure 9). TMP demonstrated a positive influence, as activity gradually increased from 45°F to approximately 62°F. In the fall, TMP was found to be of considerable importance for explaining N.humeralis activity (relative importance >0.9, Table 5 & Figure 12), as N.humeralis activity exhibited an increase at 60°F, and a peak at approximately 78°F (Figure 15) and no changes in the minimal activity recorded were observed when temperatures were below 60°F. GCC and site were of high importance, as N.humerlias activity demonstrated a positive association with GCC, increasing gradually at 0.4 and drastically at 0.42. MOON, PRCP and WS were minimally important, and CHGPRS reduced the RF model's ability to explain N.humeralis activity in the fall.

Generalized Linear Mixed Models and Multi-Model Inference

Seasonal bat models were generally in agreement with the expected relationship between bat phenology and environmental conditions, as well as the RF results, however, varied among

species and seasons. In the spring, the best supported model for E.fuscus, TMP+GCC+ (1|site), had an AIC weight of 0.30 (Table 7). Thus, full model averaging was calculated for a confidence set of seven models, consisting of models with weights greater than or equal to 0.03 (10% of the best supported model's weight). Model averaged parameter estimates from the final model, (0.04*TMP) + - (4.54*GCC) + (-0.01*WS) + (-0.27*PRCP) + (0.04*MOON) + (1|site), show a significant slight association with TMP (0.04) but no other significant associations were found (zeros were included in confidence intervals) (Table 10). Although the confidence interval included zero (-18 to 8.9), and thus, was not significant, GCC exhibited a negative influence of E.fuscus activity (-4.5), an interesting result to note. In the fall, the best supported model, GCC + CHGPRS + WS + PRCP + MOON + (1|site), had an AIC weight of 0.75 (Table 13). The resulting parameter estimates are indicative of the expected association of bat activity and environmental factors; a significant positive association with GCC (+1.3), significant negative associations with CHGPRS (-0.97) and WS (-0.86), and although not significant (confidence interval included zero), negative associations with PRCP (-0.12) and MOON (-0.31) (Table 16). The best supported model for L.borealis in the spring, TMP + GCC + (1|site), had an AIC weight of 0.76 (Table 8). Results were in agreement with the expected associations between environmental variables and L. borealis activity, as both parameters, TMP (1.37) and GCC (2.45), had positive estimates (Table 11). The best supported model in the fall, GCC+WS+(1|site), had an AIC weight of 0.26, and thus, a confidence set comprised of eight models with a weight of .026 or greater (10% top model's weight) were used for full-model averaging (Table 14). The resulting final model for L.borealis in the fall, (0.79*Intercept) + (2.23*GCC) + (0.64*WS) + (-1.08*TMP) + (-0.49*PRCP) + (-0.16*CHGPRS) + (-

0.88*MOON) + (1|site), demonstrated GCC and WS had a significant positive association with L.borealis activity, and although not significant as zero was within the confidence interval, TMP demonstrated a negative influence on activity, contradictory to expected (Table 17).

In the spring, the best supported model for N.humeralis was the global model, (0.763*Intercept) + (1.21*TMP) + (3.15*GCC) + (-0.13*WS) + (-0.26*PRCP) + (0.73*MOON) + (-0.62*CHGPRS) + (1|site), with an AIC weight of 0.84 (Table 9). Results were partially indicative of expected associations, as TMP and GCC were positively associated with N.humeralis activity, however the estimated positive influence of MOON was contrasting to expectations (Table 12). In the fall, a confidence set of four N.humeralis models with AIC weights equal to or greater than 0.04 (10% of the top model's weight) was constructed, as the best supported model, TMP + GCC + (1|site), had an AIC weight of 0.44 (Table 15). Full-model averaging resulted the final model for N.humeralis activity in the fall, (-0.82*Intercept) + (0.73*TMP) + (1.98*GCC) + (-0.64*MOON) + (0.39*WS) + (-0.22*PRCP) + (0.15*CHGPRS) + (1|site) (Table 18). Significant parameter estimates (confidence intervals that did not include zero) supported the expected associations, demonstrated by the positive influence of TMP and GCC on N.humeralis activity, and the negative influence of MOON.

Overall, the parameter estimates found to be significant in the GLMM's were comparable to the variables of importance from RF analysis. Slight discrepancies varied seasonally between species and significance with variables of importance. For example, in relation to E. fuscus activity in the spring, CHGPRS was estimated at 0 (+/- 0.01) by GLMM analysis. However, RF analysis illustrated the non-linear response of E.fuscus activity to CHGPRS (Figure 7), where activity increased with positive and negative CHGPRS values, but decreased when CHGPRS

neared zero. Thus, results may suggest that GLMM may be inadequate or limited in detecting dynamic ecological changes.

Discussion

Utilizing passive acoustic detectors to record the echolocation of bats, this study looked to identify the bat species present in the central Platte River Basin of Nebraska, the timing of seasonal fluctuations in bat activity, and the relationship between activity and ecological factors. Classification of bat calls revealed the presence of at least six species in the study area; E.fuscus, L.borealis, N.humeralis, L.cinereus, L.noctivagans, and P.subflavus. Furthermore, additional calls were classified as myotids. However, *Myotis* classifications were identified only to this genus level, as differentiating between species within this group is challenging and without extensive investigation and prior knowledge may consequently lead to erroneous identification. Of the six identified species, L.borealis, L.cinereus, and L.noctivagans are known migrants and tree-roosting species. Their distribution is widespread and documented throughout the contiguous United States including Nebraska (Geluso 2006). Therefore, the detection of these three species in the central Platte is to be expected and the findings confirm this. P.subflavus has been observed in Nebraska for over 50 years (Jones 1964). However most occurrences are documented in eastern Nebraska and have focused around mines used as hibernacula in Greeley, Cass, and Sarpy counties (Damm and Geluso 2008).

Impacts of a changing climate are predicted to affect species phenology and environmental drivers at dissimilar rates (Yang and Rudolf 2010, Johanssen 2015). Consequently, asynchronicity of phenological phases between and among species and ecological drivers have

shown to create mismatches with resource availability (Middleton et al 2013, Jones & Rebelo 2013, Forrest 2015). Across trophic levels, numerous species of plants and animals have experienced shifts in the timing of phenological phases in response to changing climatic conditions (Richardson et al. 2013, Parmesan & Yole, 2003), including vegetation phenophase and insect phenology (Dingemanse and Kalkman 2008, Ellwood et al. 2012, Schwartzberg et al. 2014). The disparate degree of phenological shifts, highlights the importance of identifying the timing of events characteristic of individual species, and understanding the interrelationship between ecological factors and phenological phases. Bats are ecological indicators (Jones et al. 2009), and thus are telling of changes within ecological systems. The limited time span and constrained spatial extent of this study was inadequate to attempt to assess or quantify shifting phenological occurrences. Therefore, this chapter looked to act as a stepping stone to establish a baseline for phenological activity of three common bat species in a region with limited knowledge of bat biology. Furthermore, the aim was to explore the relationship between bat phenology and ecological variables, with emphasis on utilizing a unique application of time-lapse imagery to obtain vegetation phenology, a proxy for resource availability.

Previous studies have demonstrated how bat activity is affected by environmental factors (Arnett et al. 2006, Baerwald & Barclay 2011, Cryan et al. 2014) and resource availability such as habitat and insects (Kusch et al. 2004, Fukui et al. 2006, Hagen 2014), on bat activity. However, the temporal frequency of habitat assessments can be sparse or time consuming to acquire, and insect availability is tedious to measure and difficult to assess (Fenton 1985, Kunz & Parsons 1988). Vegetation phenology has demonstrated applicability in understanding avian

migration and wildlife dynamics (Wiegard et al. 2008, Singh et al. 2010, Pettorelli et al. 2011) , and thus, may provide a landscape alternative to aid in assessing bat phenology.

For bats living in the Great Plains, spring and fall are transitional periods of movement; for E.fuscus movement to emerge or enter torpor, migrational movement for L.borealis, and likely migrational movement for N.humeralis. Results indicate that differences in the timing of activity during transitional periods may be attributed to species-specific phenological strategies, in observance with broad patterns of seasonality and general activity. In addition, the associations among relative bat activity and ecological factors differed between species and season, reinforcing the necessity of separating time periods and modeling species independently (Weller & Baldwin 2012). An expected observation of bat phenology, relative activity of all three species demonstrated a general increase in the spring, peak in summer, and decrease in early fall, consistent with seasonality and the findings frequent of previous literature. However, average timing of occurrence varied for individual species.

Observed discrepancies in timing and the relationship of ecological factors and activity may be indicative of species-specific life history strategies and seasonal differences in behavior. E.fuscus exhibited an earlier onset in seasonal activity compared to L.borealis and N.humeralis. As E.fuscus is a resident species, this finding isn't surprising given the uncertainty and risk associated with migration compared to hibernation. N.humeralis activity began later in the spring and ended earlier in the fall in relation to E.fuscus and L.borealis activity. The short period of activity, with a mean duration of 145 days, is telling of the elusive behavior and temporal patterns of N.humeralis compared to E.fuscus with a mean of 197 days and L.borealis with a mean of 181 days of activity during the study period. Interestingly, L.borealis activity was

recorded consistently later in the season at Rowe Sanctuary than the other two sites. This location is the most heavily forested, particularly within the local vicinity of the acoustic equipment, and given that L.borealis is a tree-roosting species, the availability of trees and/or leaf-litter may be related to the inconsistencies between sites. Moreover, two calls of L.borealis detected at Rowe Sanctuary were the latest recorded for any species during the study duration; DOY 315 (November 11) in 2013 and DOY 314 in 2014.

The importance of temperature on bat activity is well observed in the literature, and results confirm this finding although seasonal discrepancies were evident. The relationship of bat activity and temperature, established by both statistical methods, was positively associated among all three species during the spring, consistent with previous literature (Hayes 1997, Kunz 2013). Contrastingly, the results for the fall period were inconsistent with the predicted associations with temperature, as dual statistical methods found only a significant positive relationship with N.humeralis activity and no effect of temperature on L.borealis activity. This discrepancy may be attributed to the small sample size of L.borealis during the fall season or the slight non-linear response of activity to temperatures, illustrated by the partial dependence plots (Figure 14).

The observed association of moon illumination with E.fuscus and N.humeralis activity during the spring was slightly positive, which differed from the expected association. The positive relationship may be attributed to more moon illumination increasing light and improving flight visibility, as contrary to popular fables bats are not blind. Moreover, this finding may potentially be telling of habitat structure and/or predation risk within the landscape. During the

fall, E.fuscus, L.borealis, and N.humeralis activity was negatively associated with precipitation and moon illumination, supporting the expected predictions.

Supporting the hypothesized relationship, during the fall season E.fuscus, L.borealis, and N.humeralis activity was positively associated with vegetation phenology. This finding was reinforced by both regression and random forest analysis. In addition, during the spring, the activity of L. borealis and N.humeralis, a presumed migratory species, was significantly correlated with vegetation phenophase. This finding was in agreement with the a priori prediction that vegetation phenology would be associated with migratory bat activity. However, I surmised that E.fuscus activity, a resident bat species, would also be positively associated, albeit to a lesser extent. Data found an insignificant negative association between E.fuscus activity and vegetation phenology by GLMM, and comparatively, the relationship shown by RF analysis indicated an erratic response of E.fuscus activity to an increase in vegetation. Therefore, in regards to E.fuscus activity, there were idiosyncrasies between the findings and the hypothesis. During all transitional periods within the study duration, E.fuscus activity demonstrated high temporal variability and uncertainty within the findings. For example, results show a high error rate and low explanation of variance in the RF analysis, and multi-model inference of GLMMs demonstrated a wide range of AIC weights in the spring period, likely indicative of the high uncertainty associated with E.fuscus phenology. The observed variability and uncertainty, besides being inherent in ecological data, may be attributed to the robustness of the species, known for being tolerant of harsh conditions, as well as its generalist behavior (Brigham 1991). In addition, this is in agreement with the general differences in phenological trends observed, and

mentioned previously, as there is a contrasting lack of risk associated with the seasonal movement of resident species compared to migratory species.

Random forest partial dependence plots illustrate peaks, plateaus, and declines which are suggestive of potential ecological thresholds or critical points within the data (Figures 7-9, 13-15). For example, E.fuscus activity demonstrated a spring response to temperatures beginning right above freezing, and a peak increase at approximately 42°F. L.borealis activity showed a response to spring temperatures beginning at about 45°F, while partial dependence plots suggest that N.humeralis activity began gradually at approximately 48°F, but intensified at approximately 60°F. Similar responses were observed with vegetation phenology in the spring. L.borealis activity began at vegetation index 0.34, but increased instrumentally at 0.36 until it pleauted at 0.4 on the vegetation index. Similarly, N.humeralis activity responded to vegetation phenology at levels around 0.36, then activity leveled out until increasing again at 0.38 and plateauing at 0.40 on the vegetation index. This may potentially be indicative of a resource threshold or critical point, and may be worth investigating further, especially with emphasis on migratory movement. The influx and plateau pattern observed in N.humeralis and L.borealis was not observed in resident E.fuscus. Similar in both spring and fall seasons, the response of E.fuscus was more erratic and variable than L.borealis or N.humeralis.

The findings of this chapter suggest that proximal metrics of vegetation phenology may provide beneficial information and insight into bat activity and the temporal dynamics of a species that is challenging to study. Temperature is known to influence bat activity, however, results may suggest that the general effect of temperature is associated more with daily activity, and vegetation phenology may be more indicative of a directional trend related to seasonal

movement. Furthermore, the application of time-lapse imagery demonstrated potential applicability to aid in our understanding of elusive wildlife, such as N.humeralis, and the interactions of seasonal bat activity and ecological factors at a local scale. For future considerations, expanding the spatial scale to monitor vegetation phenology and survey bats across a range of latitudes may capture spatio-temporal fluctuations, patterns of bat activity and potentially migratory movement to further understand phenological interactions. Additional applications of time-lapse imagery may be advantageous in bat research to quantify vegetation complexity or tree structure to assess foraging habitat, further understand the use of forest edge, or examine water availability. For example, time-lapse imagery may provide a method to examine the change in bat activity in relation to water quantity in an ephemeral wetland or a dynamically changing aquatic system in an arid environment. As data acquisition at a range of scales is necessary to monitor and understand bat populations and habitat, time-lapse photography offers a valuable tool to assess ecological changes and interactions at a landscape scale.

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Tables & Figures

Figure 1. Map of study locations; Plum Creek Complex (PCC), Rowe River Channel (RRC), and Derr Restoration Wetland (DRW) in the Central Platte River Basin of Nebraska.

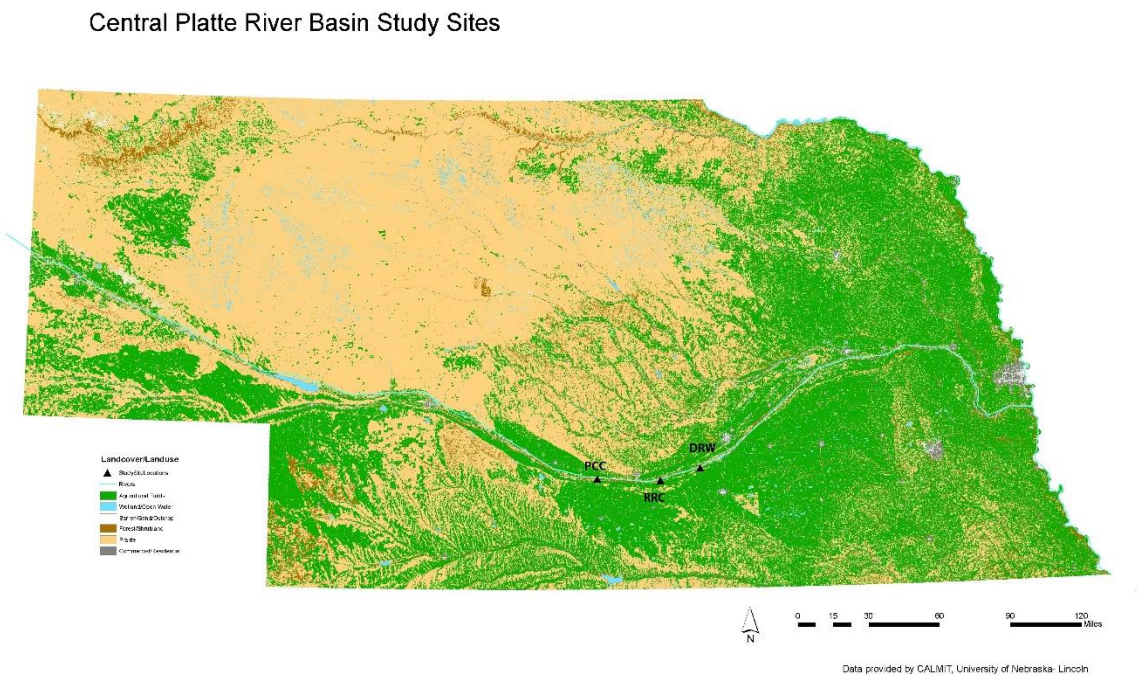

Table 1. Environmental variables used in Generalized Linear Mixed Models and Random Forest Analysis to assess relationships with bat phenology in the Central Platte River Basin, USA, from 2013 to 2015.

Variable	Units	Code	Description	Expected influence on bat phenology
Temperature	°F	TMP	Mean nightly temperature averaged from 16:00-03:00, obtained from NCDC	Positive, bat activity increases with warmer temperatures, Weller and Baldwin 2012
Green Chromatic Coordinates	Unitless	Gcc	Vegetation index derived from time-lapse imagery	Positive, a proxy for energy availability, potential cue for resource availability and surmised greater association with migrants
Wind speed	m/s	WS	Mean nightly wind speed averaged from 16:00 - 03:00 measured 1.5m above surface, obtained from NCDC	Negative, bat activity decreases with increased wind speed, Cryan et al. 2014
Moon Illumination	%	MOON	Percent of moon illuminated, obtained from U.S. Naval Observatory	Negative, decreased bat activity during high illumination due to increased predation risk, Ciechanowski 2007
Δ Pressure	mb	CHGPRS	Change in nightly mean atmospheric pressure in millibars, obtained from NCDC	Positive, changing pressure indicative of storm fronts, Baerwald & Barclay 2011
Precipitation	In	PRCP	Liquid precipitation, obtained from NCDC	Negative, rain decreases insect activity and creates unfavorable conditions for flight, Parsons et al. 2003

Table 2. Summary statistics of bat activity and ecological variables during the spring and fall season for 2013, 2014, and 2015 at three locations in the Central Platte River Basin, NE.

	Variable	N	Mean	Minimum	Maximum	Standard Deviation
Spring	L.borealis	290	14	0	192	27
	E.fuscus	290	25	0	282	53
	N.humeralis	290	9	0	150	21
	Pressure	290	-0.10	-11	13	5
	Wind speed	290	13.03	4.50	29.30	4.37
	Temperature	290	53	21	76	11
	Precipitation	290	0.04	0.00	1.86	0.16
	Gcc	290	0.36	0.33	0.45	0.03
	Moon	290	0.50	0.00	1.00	0.35
Fall	L.borealis	172	2.8	0	42	5.96
	E.fuscus	172	8.2	0	256	25.6
	N.humeralis	172	1.3	0	29	3.38
	Pressure	172	0.004	-10.45	12.45	4.2
	Wind speed	172	10.14	1.4	21.4	3.5
	Temperature	172	61.4	26.60	84.00	12.10
	Precipitation	172	0.03	0.00	0.80	0.11
	Gcc	172	0.41	0.33	0.44	0.02
	Moon	172	0.46	0	1	0.35

Figure 2. Relative activity of L.borealis (Red Bat, *Lasiurus borealis)*, E.fuscus (Big Brown Bat, *Eptesicus fuscus*), and N.humeralis (Evening Bat, *Nycticeius humeralis)* obtained from passive acoustic surveys during duration of study, 2013, 2014, and 2015, at three study sites, Derr, Plum, and Rowe, in the Central Platte River Basin of Nebraska. Due to technicalities, data from Derr in 2013 has been omitted. Colors donate season. Although not included in analysis, summer activity is illustrated here for visual assessment of activity.

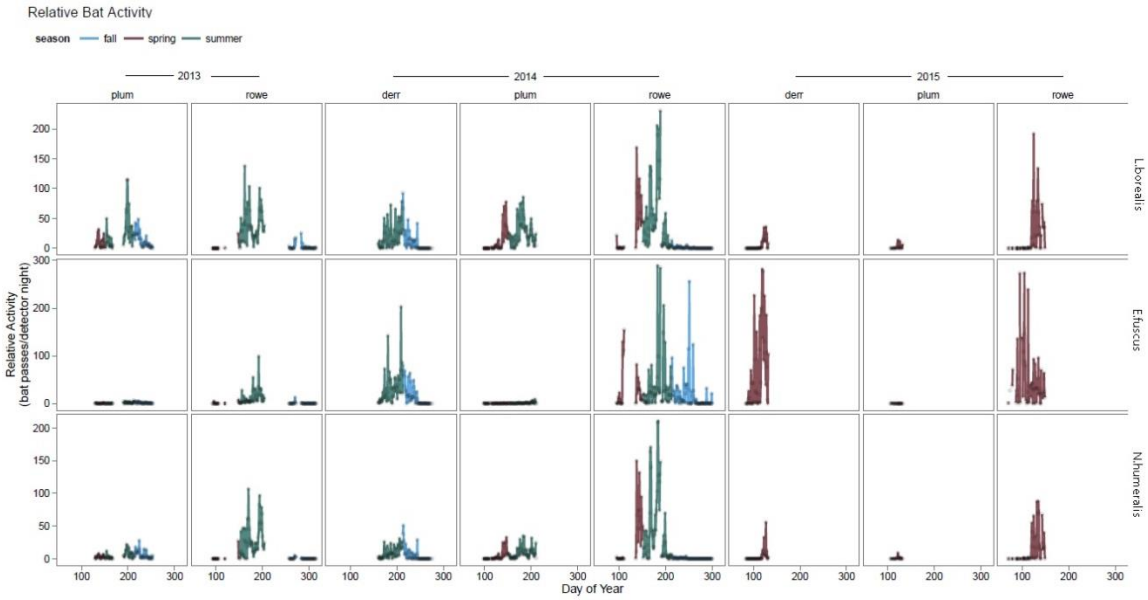

Figure 3. Ecological variables used in analysis to assess the relationship with bat activity at three study sites during the spring of 2013, 2014, and 2015, and the fall of 2013 and 2014. Summer was not analyzed, but included in graphic for visual assessment. Color denotes season.

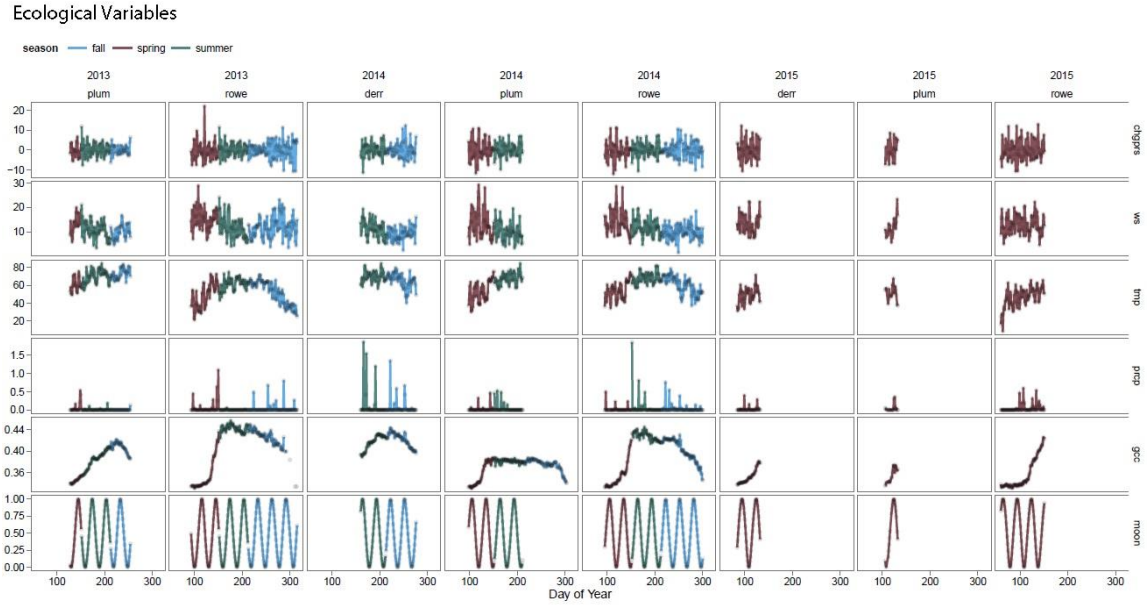

Table 3. Metrics of Random Forest Analysis used in spring analysis to assess relationship between environmental variables and bat phenology. N is the number of samples, # Trees were the quantity of trees constructed in the forest analysis, % Variance is the percent of variance explained by each model, and the Error Rate is the MSE from Out-of-bag samples.

RF Metrics	E.fuscus	L.borealis	N.humeralis
N	254	254	254
# Trees	1000	1000	1000
% Variance	25.17	37.69	39.84
Error Rate	2181.19	471.7	276.87

Figure 4. Ranked parameters and variable importance determined by Random Forest E.fuscus model used to assess relationship with bat phenology in the spring period.

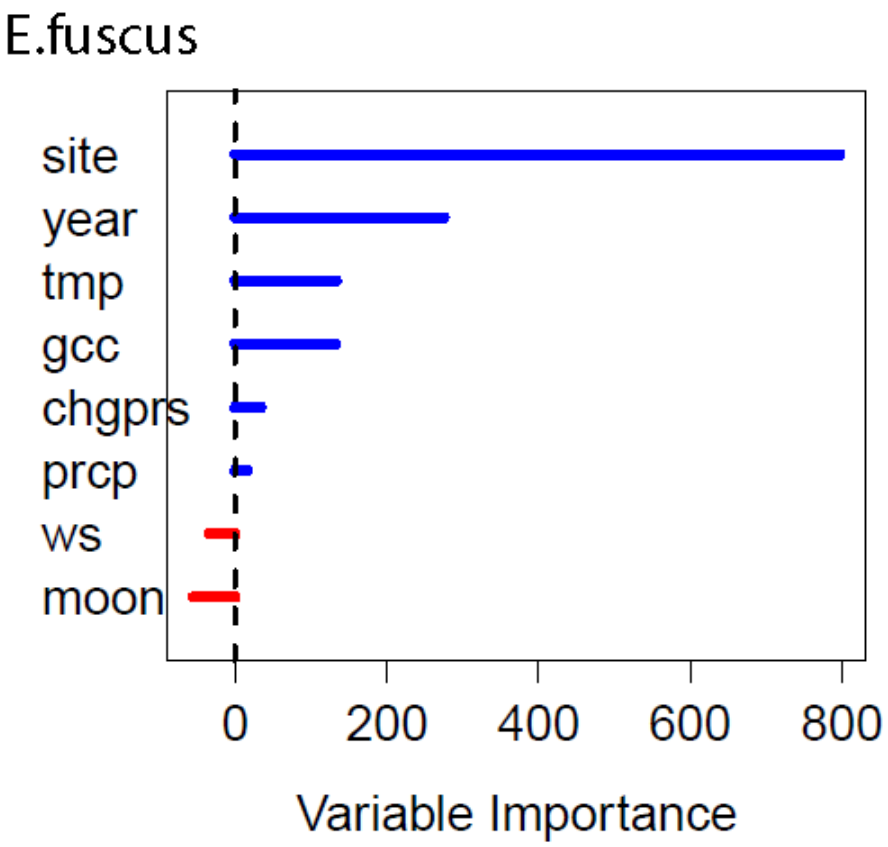

Figure 5. Ranked parameters and variable importance determined by Random Forest L.borealis model used to assess relationship with bat phenology in the spring period.

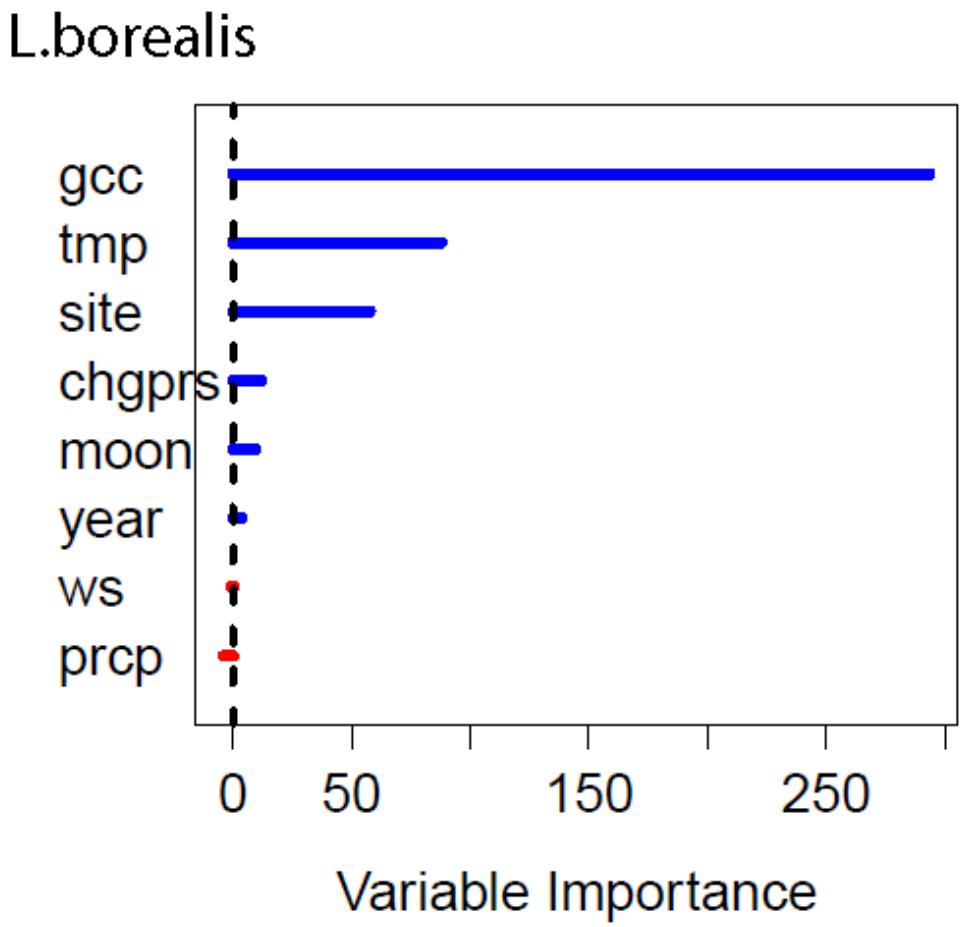

Figure 6. Ranked parameters and variable importance determined by Random Forest N.humeralis model used to assess relationship with bat phenology in the spring period.

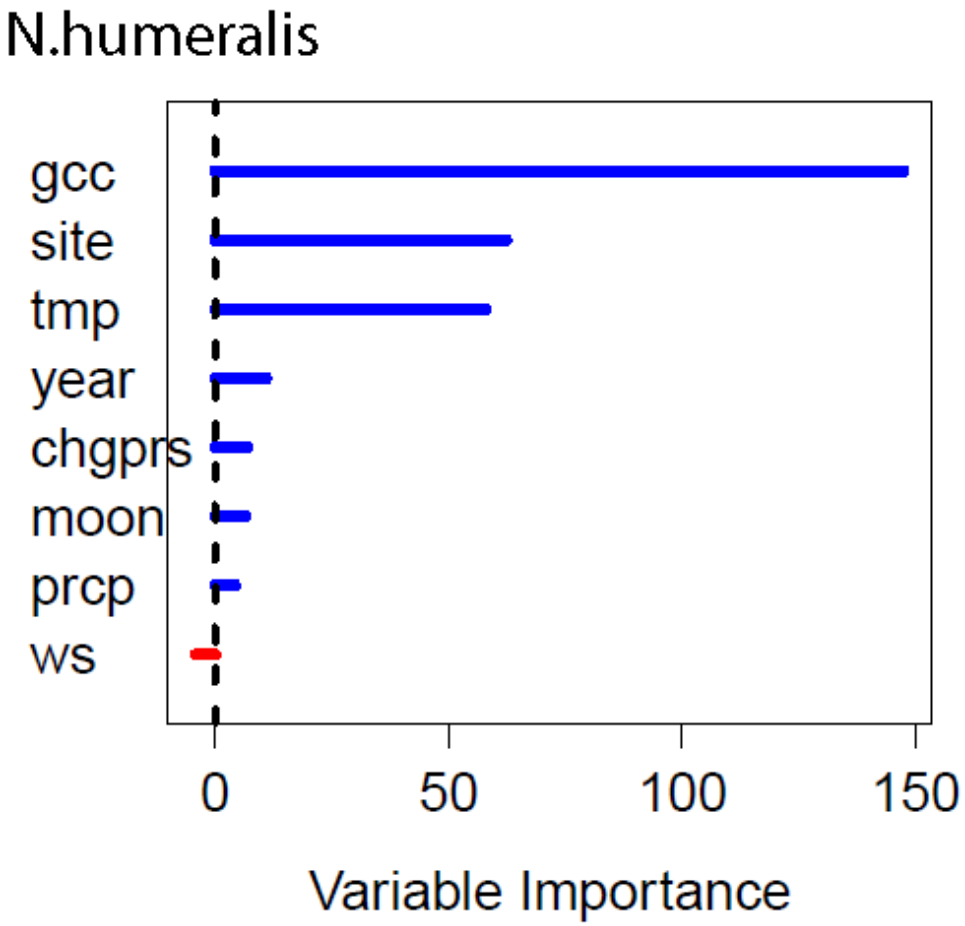

Table 4. Parameters used in Random Forest models to assess relationship with bat phenology in the spring period ranked by importance scores based on permutation of OOB data.

	Parameter	Importance	Relative Importance
E.fuscus			
	Site	797.2	1.00
	Year	275.7	0.35
	TMP	133.5	0.17
	GCC	131.8	0.17
	CHGPRS	33.9	0.04
	PRCP	16.3	0.02
	WS	-33.9	-0.04
	MOON	-55.0	-0.07
L.borealis			
	GCC	293.5	1.00
	TMP	87.7	0.30
	Site	57.7	0.20
	CHGPRS	11.9	0.04
	MOON	9.7	0.03
	Year	3.8	0.01
	WS	-0.6	0.00
	PRCP	-3.8	-0.01
N.humeralis			
	GCC	216.5	1.00
	Site	104.9	0.48
	TMP	68.9	0.32
	MOON	22.9	0.11
	Year	17.3	0.08
	CHGPRS	4.3	0.02
	PRCP	0.1	0.00
	WS	-0.5	0.00

Figure 7. Random Forest partial dependence plots illustrating the influence of individual parameters on E.fuscus activity during the spring given all other variables held at constant mean. Red dashed lines indicate +/- two standard errors.

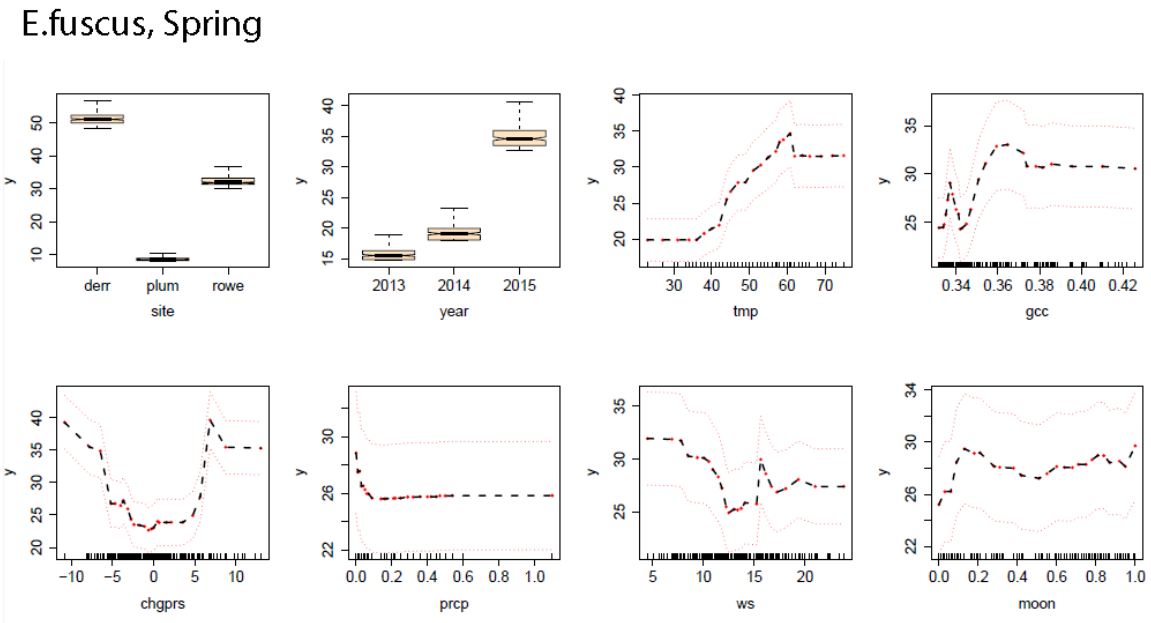

Figure 8. Random Forest partial dependence plots illustrating the influence of individual parameters on L.borealis activity during the spring given all other variables held at constant mean. Red dashed lines indicate +/- two standard errors.

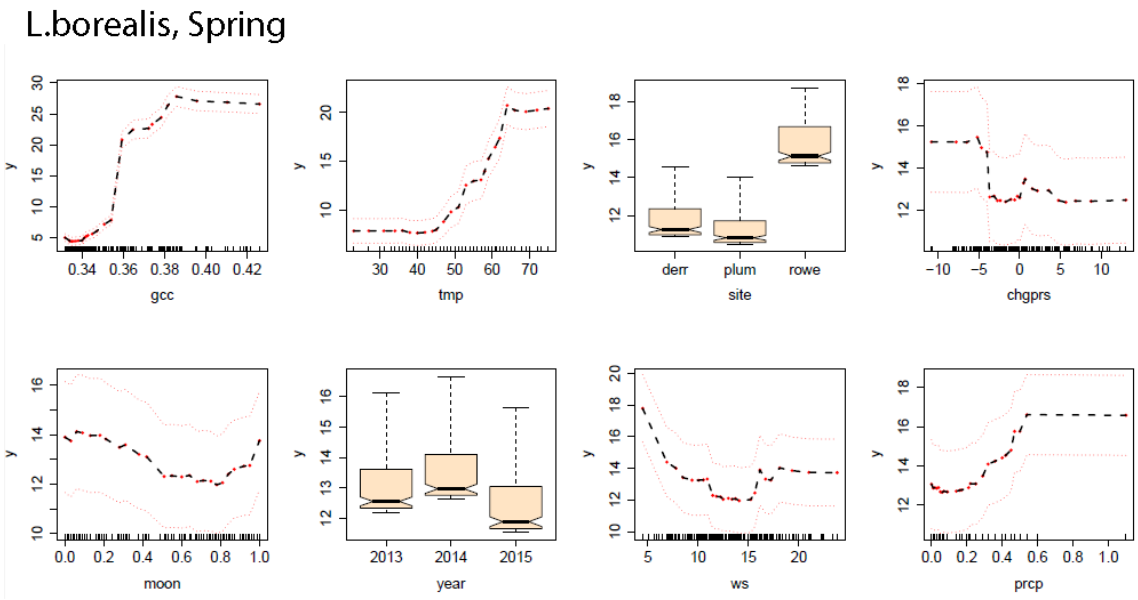

Figure 9. Random Forest partial dependence plots illustrating the influence of individual parameters on N.humeralis activity during the spring given all other variables held at constant mean. Red dashed lines indicate +/- two standard errors.

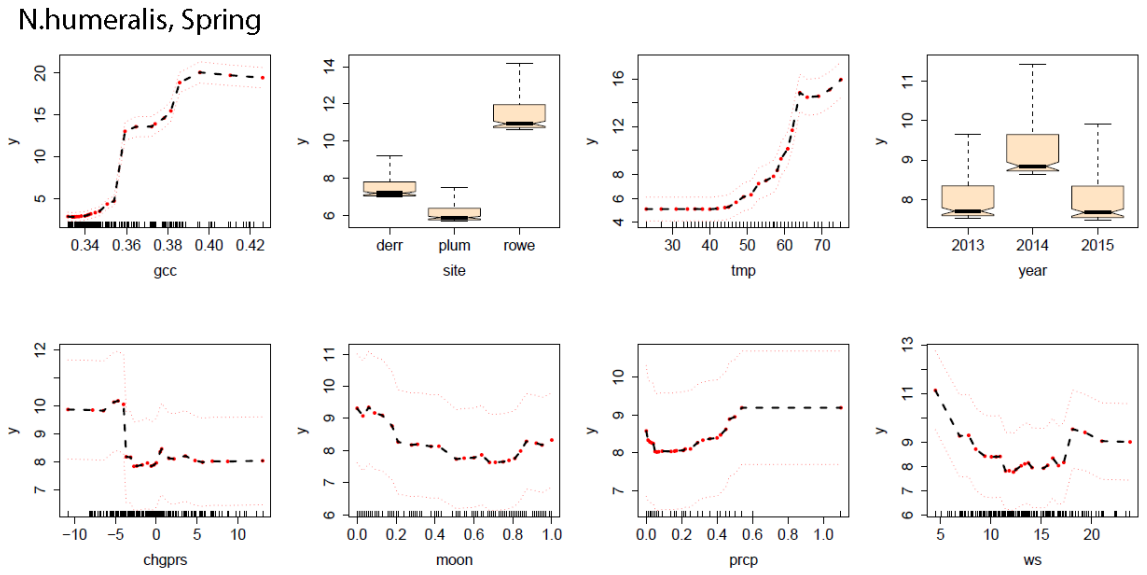

Figure 10. Ranked parameters and variable importance determined by Random Forest E.fuscus model used to assess relationship with bat phenology in the fall period.

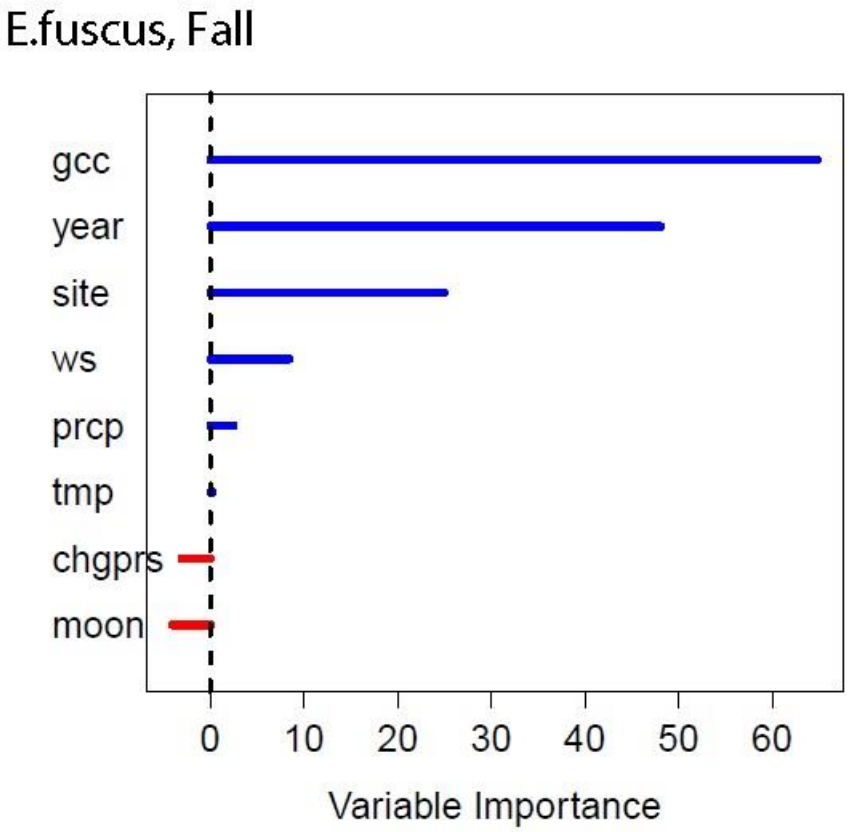

Figure 11. Ranked parameters and variable importance determined by Random Forest L.borealis model used to assess relationship with bat phenology in the fall period.

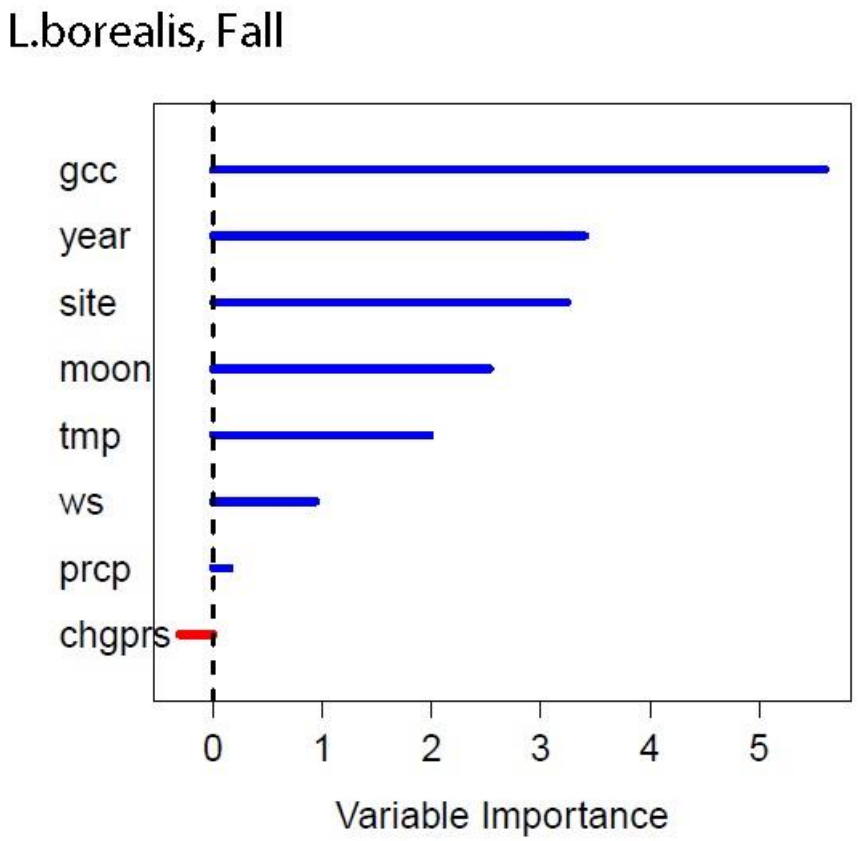

Figure 12. Ranked parameters and variable importance determined by Random Forest N.humeralis model used to assess relationship with bat phenology in the fall period.

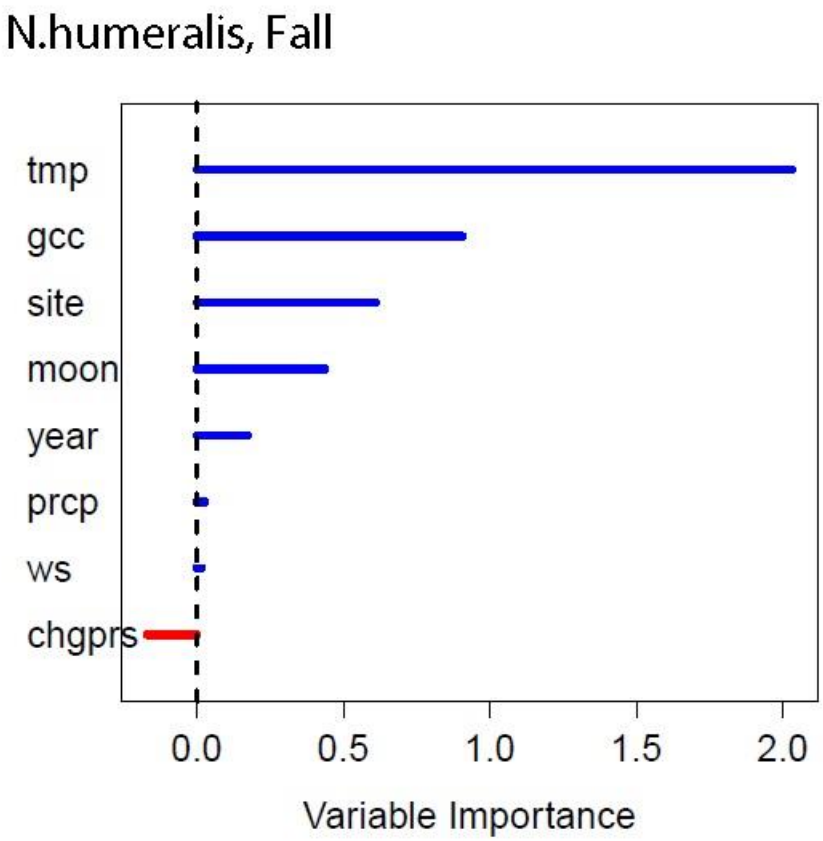

Table 5. Parameters used in Random Forest models to assess relationship with bat phenology in the fall period ranked by importance scores based on permutation of OOB data.

	Parameter	Importance	Relative Importance
E.fuscus	GCC	64.76	1.00
	Year	48.06	0.74
	Site	24.92	0.38
	WS	8.38	0.13
	PRCP	2.49	0.04
	TMP	0.25	0.00
	CHGPRS	-3.08	-0.05
	MOON	-4.01	-0.06
L.borealis			
	GCC	5.60	1.00
	Year	3.40	0.61
	Site	3.24	0.58
	MOON	2.53	0.45
	TMP	1.98	0.35
	WS	0.93	0.17
	PRCP	0.15	0.03
	CHGPRS	-0.31	-0.05
N.humeralis			
	TMP	2.03	1.00
	GCC	0.91	0.45
	Site	0.61	0.30
	MOON	0.34	0.12
	Year	0.17	0.09
	PRCP	0.03	0.01
	WS	0.02	0.01
	CHGPRS	-0.17	-0.08

Figure 13. Random Forest partial dependence plots illustrating the influence of individual parameters on E.fuscus activity during the fall given all other variables held at constant mean. Red dashed lines indicate +/- two standard errors.

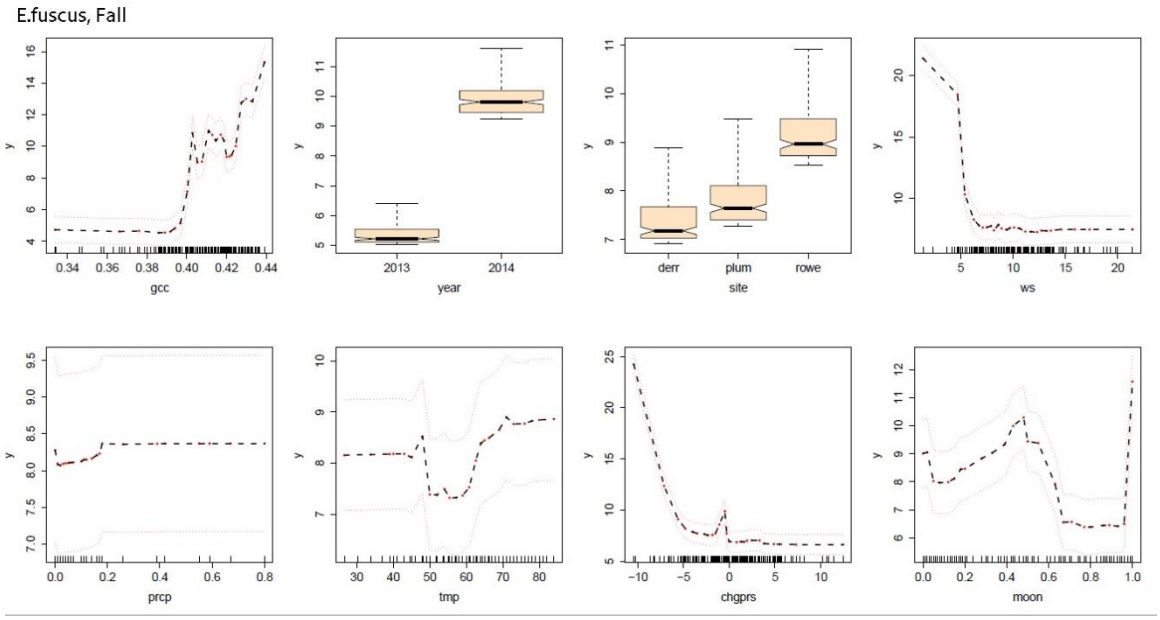

Figure 14. Random Forest partial dependence plots illustrating the influence of individual parameters on L.borealis activity during the fall given all other variables held at constant mean. Red dashed lines indicate +/- two standard errors.

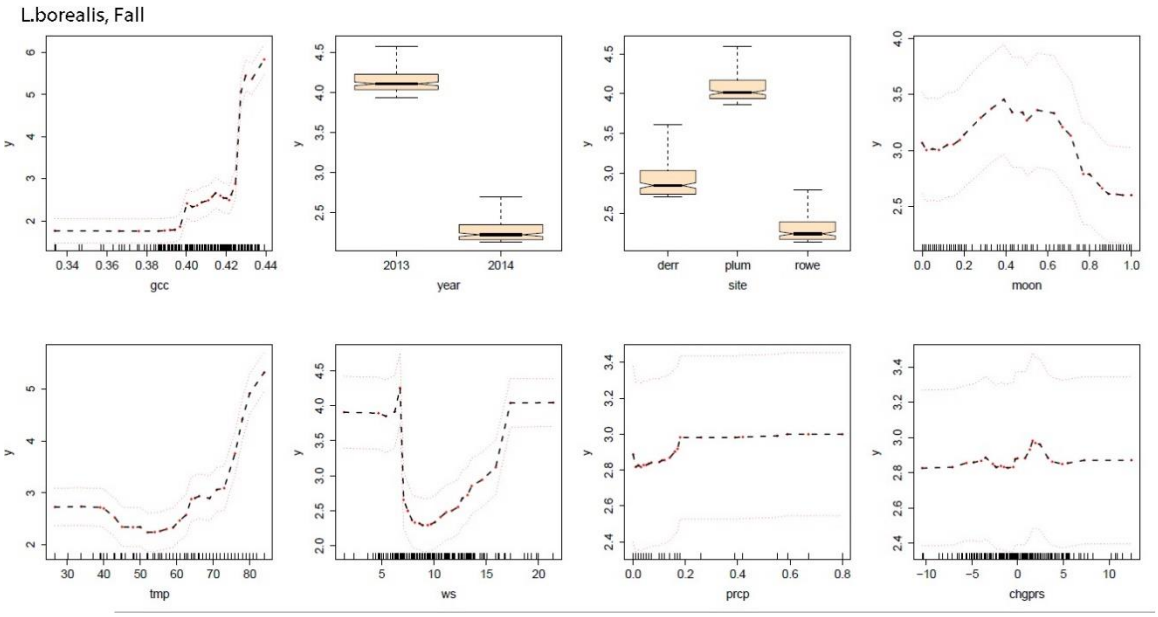

Figure 15. Random Forest partial dependence plots illustrating the influence of individual parameters on N.humeralis activity during the fall given all other variables held at constant mean. Red dashed lines indicate +/- two standard errors.

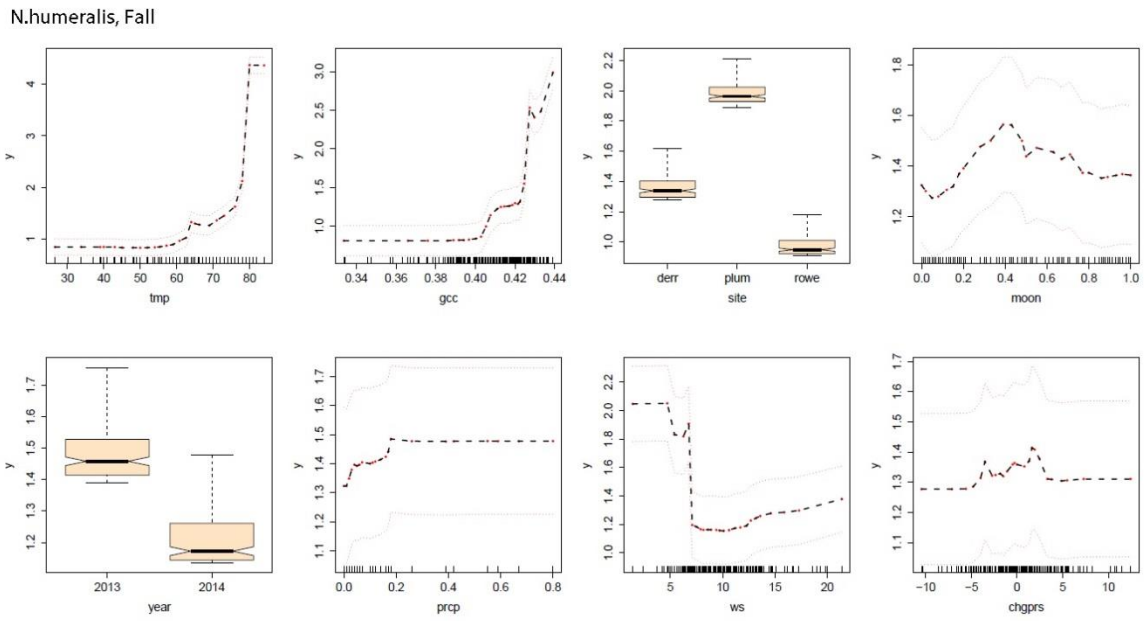

Table 6. Candidate suite of negative binomial generalized linear mixed models used to assess the relationship between environmental variables and bat phenology. Site was included in each model as a random effect. Analysis was run separately for species (E.fuscus, L.borealis, N.humeralis) and season (spring, fall) using the candidate suite of models.

Candidate Models
Null
TMP + GCC + WS + PRCP + MOON + CHGPRS (Global)
TMP + CHGPRS + WS + PRCP + MOON
GCC + CHGPRS+ WS + PRCP + MOON
TMP + CHGPRS
GCC + CHGPRS
TMP + MOON
GCC + MOON
TMP + PRCP
GCC + PRCP
TMP + WS
GCC + WS
TMP + GCC
TMP
GCC

Table 7. E.fuscus model results from multi-model inference model selection during the spring period ranking the best fit models based on Akaike weights. A suite of 15 models were run separately for species. Site was included as a random effect in each model, allowing the intercept to vary between research sites. E.fuscus confidence set based on models with 10% of top model weight are in bold.

Model	K	AICc	ΔAIC	ω_i
TMP + GCC	**5**	**1480.02**	**0.00**	**0.30**
TMP	**4**	**1481.31**	**1.29**	**0.16**
TMP + WS	**5**	**1481.62**	**1.60**	**0.14**
TMP + PRCP	**5**	**1481.80**	**1.78**	**0.12**
TMP + MOON	**5**	**1482.99**	**2.97**	**0.07**
TMP + CHGPRS	**5**	**1483.26**	**3.24**	**0.06**
TMP + GCC + WS + PRCP + MOON + CHGPRS	**9**	**1483.79**	**3.77**	**0.05**
Null	3	1484.88	4.86	0.03
TMP + CHGPRS + WS + PRCP + MOON	8	1485.05	5.03	0.02
GCC + WS	5	1485.71	5.69	0.02
GCC	4	1486.32	6.30	0.01
GCC + PRCP	5	1487.63	7.61	0.01
GCC + MOON	5	1487.98	7.96	0.01
GCC + CHGPRS	5	1488.10	8.08	0.01
GCC + CHGPRS+ WS + PRCP + MOON	8	1489.60	9.58	0.00

Table 8. L.borealis model results from multi-model inference model selection during the spring period ranking the best fit models based on Akaike weights. A suite of 15 models were run separately for species. Site was included as a random effect in each model, allowing the intercept to vary between research sites. L.borealis top model is in bold.

Model	K	AICc	ΔAIC	ω_i
TMP + GCC	**5**	**1315.79**	**0.00**	**0.76**
TMP + GCC + WS + PRCP + MOON + CHGPRS	9	1318.12	2.33	0.24
GCC + CHGPRS	5	1327.58	11.79	0.00
GCC + CHGPRS+WS+PRCP+MOON	8	1330.28	14.49	0.00
GCC + MOON	5	1330.69	14.90	0.00
GCC	4	1332.20	16.41	0.00
GCC + PRCP	5	1334.16	18.37	0.00
GCC + WS	5	1334.28	18.49	0.00
TMP	4	1354.27	38.48	0.00
TMP + MOON	5	1355.70	39.92	0.00
TMP + PRCP	5	1355.93	40.14	0.00
TMP + WS	5	1356.19	40.40	0.00
TMP + CHGPRS	5	1356.28	40.49	0.00
TMP + CHGPRS+ WS + PRCP + MOON	8	1360.63	44.84	0.00
Null	3	1394.61	78.82	0.00

Table 9. N.humeralis model results from multi-model inference model selection during the spring period ranking the best fit models based on Akaike weights. A suite of 15 models were run separately for species. Site was included as a random effect in each model, allowing the intercept to vary between research sites. N.humeralis top model is in bold.

Model	K	AICc	ΔAIC	ω_i
TMP + GCC + WS + PRCP + MOON + CHGPRS	**9**	**1075.76**	**0.00**	**0.84**
TMP + GCC	5	1079.12	3.36	0.16
GCC + CHGPRS+WS+PRCP+MOON	8	1087.93	12.17	0.00
GCC + CHGPRS	5	1088.68	12.92	0.00
GCC + MOON	5	1090.75	14.99	0.00
GCC	4	1095.96	20.20	0.00
GCC + PRCP	5	1096.93	21.17	0.00
GCC + WS	5	1098.02	22.26	0.00
TMP	4	1124.79	49.03	0.00
TMP + MOON	5	1126.03	50.27	0.00
TMP + WS	5	1126.53	50.77	0.00
TMP + CHGPRS	5	1126.81	51.05	0.00
TMP + PRCP	5	1126.87	51.11	0.00
TMP + CHGPRS+WS+PRCP+MOON	8	1131.03	55.27	0.00
Null	3	1168.93	93.17	0.00

Table 10. Model averaged estimates of parameters in the confidence set for E.fuscus activity during the spring. Confidence set included seven models with an Akaike's Information Criterion corrected for small sample size (AICc) weight of at least 10% within the best supported model (Table 7).

Parameter	Estimate	Standard Error	LCI*	UCI*
Intercept	1.56	2.76	-3.86	6.98
TMP	0.04	0.02	0.01	0.08
GCC	-4.54	6.87	-18.01	8.93
WS	-0.01	0.03	-0.06	0.04
PRCP	-0.27	0.73	-1.70	1.16
MOON	0.04	0.17	-0.30	0.38
CHGPRS	0.00	0.01	-0.02	0.02

*LCI; lower 95% confidence interval of parameter estimate, UCI; upper 95% confidence interval of parameter estimate

Table 11. Estimates of parameters from model selected as best fit using Akaike's Information Criterion corrected for small sample size (AICc) for L.borealis activity during the spring. Top model included site as a random effect.

Parameter	Estimate	Standard Error	LCI*	UCI*
Intercept	1.57	0.28	.76	2.31
TMP	1.37	0.32	0.76	1.99
GCC	2.45	0.38	1.71	3.22

*LCI; lower 95% confidence interval of parameter estimate, UCI; upper 95% confidence interval of parameter estimate

Table 12. Estimates of parameters from model selected as best fit using Akaike's Information Criterion corrected for small sample size (AICc) for N.humeralis activity during the spring. Top model included site as a random effect.

Parameter	Estimate	Standard Error	LCI*	UCI*
Intercept	0.73	0.33	-0.21	1.63
TMP	1.21	0.33	0.59	1.87
GCC	3.15	0.40	2.38	3.95
WS	-0.13	0.33	-0.80	0.51
PRCP	-0.26	0.26	-0.74	0.31
CHGPRS	-0.62	0.30	-1.21	-0.02
MOON	0.73	0.31	0.13	1.34

*LCI; lower 95% confidence interval of parameter estimate, UCI; upper 95% confidence interval of parameter estimate

Table 13. E.fuscus model results from multi-model inference model selection during the fall period ranking the best fit models based on Akaike weights. A suite of 15 models were run separately for species. Site was included as a random effect in each model, allowing the intercept to vary between research sites. Best fit model is in bold.

Model	K	AICc	ΔAIC	ω_i
GCC + CHGPRS+ WS + PRCP + MOON	**8**	**749.70**	**0.00**	**0.75**
TMP + GCC + WS + PRCP + MOON + CHGPRS	9	751.92	2.22	0.25
GCC+WS	5	762.40	12.70	0.00
GCC+CHGPRS	5	763.35	13.65	0.00
TMP + CHGPRS+ WS + PRCP + MOON	8	764.26	14.56	0.00
TMP+WS	5	765.77	16.07	0.00
GCC	4	769.11	19.41	0.00
TMP+GCC	5	769.64	19.95	0.00
GCC+PRCP	5	770.48	20.78	0.00
GCC+MOON	5	770.99	21.29	0.00
TMP	4	773.14	23.44	0.00
TMP+CHGPRS	5	773.57	23.87	0.00
TMP+MOON	5	774.59	24.89	0.00
TMP+PRCP	5	775.00	25.30	0.00
Null	3	778.43	28.73	0.00

Table 14. L.borealis model results from multi-model inference model selection during the spring period ranking the best fit models based on Akaike weights. A suite of 15 models were run separately for species. Site was included as a random effect in each model, allowing the intercept to vary between research sites. L.borealis confidence set based on models with 10% of top model weight are in bold.

Model	K	AICc	ΔAIC	ω_i
GCC+WS	**5**	**612.13**	**0.00**	**0.26**
TMP + GCC + WS + PRCP + MOON + CHGPRS	**9**	**612.31**	**0.18**	**0.24**
GCC	**4**	**613.39**	**1.27**	**0.14**
GCC+MOON	**5**	**614.08**	**1.96**	**0.10**
TMP+GCC	**5**	**614.21**	**2.08**	**0.09**
GCC+PRCP	**5**	**614.95**	**2.83**	**0.06**
GCC + CHGPRS+ WS + PRCP + MOON	**8**	**615.40**	**3.27**	**0.05**
GCC+CHGPRS	**5**	**615.51**	**3.39**	**0.05**
Null	3	626.26	14.14	0.00
TMP	4	627.36	15.23	0.00
TMP+WS	5	627.39	15.27	0.00
TMP+CHGPRS	5	629.17	17.05	0.00
TMP+MOON	5	629.30	17.17	0.00
TMP+PRCP	5	629.48	17.35	0.00
TMP + CHGPRS+ WS + PRCP + MOON	8	633.35	21.22	0.00

Table 15. N.humeralis model results from multi-model inference model selection during the spring period ranking the best fit models based on Akaike weights. A suite of 15 models were run separately for species. Site was included as a random effect in each model, allowing the intercept to vary between research sites. N.humeralis confidence set based on models with 10% of top model weight are in bold.

Model	K	AICc	ΔAIC	ω_i
TMP+GCC	**5**	**402.19**	**0.00**	**0.44**
GCC+MOON	**5**	**403.65**	**1.47**	**0.21**
TMP + GCC + WS + PRCP + MOON + CHGPRS	**9**	**403.69**	**1.50**	**0.21**
GCC + CHGPRS+ WS + PRCP + MOON	**8**	**404.93**	**2.75**	**0.11**
GCC	4	409.01	6.82	0.01
GCC+PRCP	5	410.23	8.04	0.01
GCC+WS	5	410.72	8.53	0.01
GCC+CHGPRS	5	411.13	8.94	0.01
TMP	4	423.79	21.60	0.00
TMP+CHGPRS	5	424.72	22.53	0.00
TMP+PRCP	5	425.57	23.38	0.00
TMP+MOON	5	425.88	23.69	0.00
TMP+WS	5	425.88	23.70	0.00
TMP + CHGPRS+ WS + PRCP + MOON	8	430.76	28.58	0.00
Null	3	440.75	38.57	0.00

Table 16. Estimates of parameters from model selected as best fit using Akaike's Information Criterion corrected for small sample size (AICc) for E.fuscus activity during the fall. Top model included site as a random effect.

Parameter	Estimate	Standard Error	LCI*	UCI*
Intercept	0.78	0.55	-0.80	2.23
GCC	1.30	0.26	1.63	3.66
CHGPRS	-0.97	0.22	-2.83	-1.10
WS	-0.86	0.20	-2.50	-0.93
PRCP	-0.12	0.18	-0.87	0.65
MOON	-0.31	0.23	-1.56	0.29

Table 17. Model averaged estimates of parameters in the confidence set for L.borealis activity during the fall. Confidence set included seven models with an Akaike's Information Criterion corrected for small sample size (AICc) weight of at least 10% within the best supported model (Table 14).

Parameter	Estimate	Standard Error	LCI*	UCI*
Intercept	0.79	0.49	-0.18	1.76
GCC	2.23	0.74	0.76	3.69
WS	0.64	0.32	0.01	1.27
TMP	-1.08	0.61	-2.29	0.13
PRCP	-0.49	0.34	-1.17	0.19
CHGPRS	-0.16	0.44	-1.02	0.70
MOON	-0.88	0.52	-1.90	0.13

Table 18. Model averaged estimates of parameters in the confidence set for N.humeralis activity during the fall. Confidence set included seven models with an Akaike's Information Criterion corrected for small sample size (AICc) weight of at least 10% within the best supported model (Table 15).

Parameter	Estimate	Standard Error	LCI*	UCI*
Intercept	-0.82	0.70	-2.20	0.56
TMP	0.73	0.31	0.12	1.34
GCC	1.98	0.60	0.80	3.16
MOON	-0.64	0.27	-1.17	-0.12
WS	0.39	0.20	-0.01	0.78
PRCP	-0.22	0.19	-0.60	0.16
CHGPRS	0.15	0.24	-0.32	0.62

Chapter 5. An Assessment of Vegetation Phenology in the Great Plains of Nebraska Using Time-lapse Imagery

Introduction

Global change across various spatio-temporal scales have increased the necessity of monitoring natural systems to guide management and mitigate impacts of a rapidly changing world. A valuable component for understanding environmental change, phenology is defined as the timing of cyclical biological occurrences, their biotic and abiotic drivers, and the synchronicity of phases between and among species (Lieth 1974). Climate-induced changes have been observed in the phenological timing of many species and their environments (Cleland et al. 2012, Thackeray et al. 2010), increasing the need to acquire data and measure ecological responses to global change at multiple scales.

The growing cognizance of a changing climate and attention to forecasting the resulting implications on ecological systems has heightened the importance and progressed the associated methodologies, tools, and scales of phenological observation (Forrest 2015). Time-lapse imagery, or repeat photography, has emerged as a valuable tool for augmenting scales of data acquisition and assessing environmental change, particularly for assessing vegetation phenology. A primary aspect of ecological functioning, vegetation phenophase is an indicator of primary productivity and energy availability through direct and indirect attainment (Jetz et al. 2009, Yang et al. 2010, Toomey 2015, Weigand 2008). Thus, vegetation influences the entire food web and is essential to derive a baseline understanding of the functional aspects of ecosystem dynamics, particularly in the face of global climate change (McNaughton et al. 1989, Ellwood et al. 2012, Richardson et al. 2013, Pettorelli et al. 2011).

Historically, vegetation phenology was examined by human observation or measurement of biomass by clipping and weighing plant matter. These traditional methodologies are still useful as they provide species specific measurements, however, the spatial and temporal frequency of data collection is limited, time consuming, labor intensive, subjective, and cannot be validated at a later date (White et al. 2005, Coops et al. 2012). Contrastingly, satellite remote sensing offers vast quantities of data with minimal labor requirements and a global to regional spatial extent. Satellite vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) [equation 1] calculated from near-infrared wavelengths (700-1400 nm), provides a large-scale proxy for photosynthetically active period (Toomey 2015), gross primary production (Pettorelli et al 2011), leaf area index (Carlson & Ripley 1997), food availability (Pettorelli et al. 2005), and is an important tool in wildlife ecology (Petorelli et al. 2010). However, limitations imposed by satellite-based monitoring can be restrictive for analysis; moderately infrequent temporal intervals of data acquisition, sensitivity to atmospheric disturbance and cloud cover, and a scale and resolution trade-off (White et al., 2009, Ide and Oguma 2010). For example, the coarse spatial resolution of the Moderate Resolution Imaging Spectradiometer (MODIS) is collected at 250-500m with repeat intervals every 1-2days, while the satellite platform Landsat 8 has temporal resolution of 16 days and a spatial resolution of 15-30m (landsat.usgs.gov).

To accurately assess vegetation phenology and ecological functioning, it is necessary to bridge the observational disconnect between human documentation and satellite remote sensing. Ground-based sensing (also referred to as proximal or in-situ) using digital time-lapse camera systems, provides a technique to satisfy a data gap between human and satellite observation, amplify monitoring at a wider range of scales, and to validate satellite remote sensing (Saitoh et

al. 2012). The controllability of time-lapse systems allows for specification of time intervals (i.e. one image every ten minutes or one image every day), and a degree of spatial designation up to regions (i.e. leaf, plant, community, landscape), to adapt data acquisition in regard to site-based assessments. Thus, the specificity of ground-based monitoring is advantageous for measuring changes that take place in delineated ranges, such as addressing research-guided land management, and for assessing numerous aspects of vegetation, including biomass (Sakamoto et al. 2012), vegetation cover (Nguy-Robertson et al. 2013), gross primary productivity (Saitoh et al. 2012), leaf phenology (Ahrends et al. 2009), and photosynthesis in forests (Richardson et al 2007) and grassland ecosystems (Migliavacca et al 2011).

The timing of vegetation phenophase is driven by interacting factors such as photoperiod, temperature, soil water content, snow-melt, moisture, and regional climatic changes (Singh and Kushwaha 2005, Huete et al. 2006, Cleland et al. 2006, Julitta et al. 2014). Changes in the timing of vegetation phenology have been observed as earlier flowering (Miller-Rushing and Primack 2008), tree leaf-out (Thompson and Clark 2008), delays in foliage color (Menzel et al. 2008) and senescence (Delpierre et al 2009). Thus, observed changes in vegetation phenophase are suggestive of shifting seasonal patterns and inter-annual climatic variations (Dunn & Beurs 2011, Xiao and Moody 2004).

The objective of this chapter is to assess the relationship between ground-based and satellite derived vegetation metrics and derive phenometrics from time-lapse imagery to characterize vegetation changes. Digital time-lapse camera stations, in collaboration with the Platte Basin Timelapse Project (PBT; www.plattebasintimelapse.com), were used to document changes in floodplain vegetation within a water-stressed system of the Great Plains of Nebraska.

PBT has archived over half a million images throughout the Platte Basin watershed, offering an immense collection of data and potential insight into environmental change and water-stressed landscapes.

Methods

Study area

The primary study area was located in south-central Nebraska, within a ~90km section of the central Platte River Basin extending from Lexington, Nebraska, USA, eastward to Grand Island. A leading agro-ecosystem, the Central Platte River Basin is dominated by agriculture of largely maize-soybean rotation, which accounts for ~49% of land use (Brei 2005). Grasslands cover an additional 24%, followed by an accumulated 15 % of wet meadow, development, and riparian woodland. Historically, the Platte River Basin was characterized by sand dominated, shallow and braided channels. However, reduction in streamflow and sediment scouring has encouraged vegetation growth on surrounding riparian areas, resulting an abundance of invasive species such as Purple loosestrife (*Lythrum salicaria)*, Common Reed (*Phragmites*), Eastern Red Cedar (*Juniperus virginiana*), and Russian Olive (*Elaeagnus angustifolia*).

Data was collected from three research sites within the central Platte River Basin; Plum Creek Complex (PCC), Rowe River Channel (RRC), and Derr Restoration (DRW) (Figure 1). PCC (40.679, -99.401667) near the town of Overton, Nebraska, is the furthest west location, situated on the south channel of the Platte River. RRC (40.6675, -98.8924), near Gibbon, Nebraska, is maintained by the National Audubon Society and adjacent to the Platte River's south channel. The site is characterized by riparian wetlands, forested patches, and agricultural fields. DRW (40.74102, -98.57278), near Wood River, Nebraska, is a section of the Platte River

Prairies tract of land owned and managed by The Nature Conservancy (TNC). In 2011, a wetland slough situated on the tract of native prairie was restored from a sand and gravel mining pit.

Time-lapse Camera Systems

At each site a high resolution DSLR time-lapse camera was installed approximately three to four meters on a wooden pole in collaboration with the Platte Basin Timelapse project (PBT) (Figure 2). A red-green-blue (RGB) color channel image was captured every hour between sunrise and sunset. The images were automatically uploaded to PBT's 1.5 terra-byte image library and selected through Phocalstream, software technology developed by the Jeffrey S.Raikes School for Computer Science and Management at the University of Nebraska – Lincoln. Three images a day were selected between the hours of 10:00 and 14:00 for standardization and manually vetted for discrepancies within the frame of view (rain drops on lens, camera movement, etc.). Images were discarded if discrepancies were present, and if possible, replaced by another image between the house of 10:00 and 14:00 to complete the three-image sequence.

Green Chromatic Coordinate (Gcc)

To assess vegetation phenophase, a standard, site specific, region of interest (ROI) encompassing only vegetation was selected within the images. At RRC, the ROI selected woody vegetation along the river bank at a distance of 130m (Figure 3). The ROI at DRW encompassed tallgrass prairie, approximately 190m from the vegetation within the ROI and the camera station (Figure 4). At PCC, the ROI selected a forested riparian zone at a distance of approximately 300m from the camera system (Figure 5). Within each ROI, the average digital number for each Red-Green-Blue (RGB) color channel was used to calculate the Green Chromatic Coordinate

(Gcc) vegetation index (Wyszecki and Stiles 1982, Gillespie et al. 1987, Sonnentag et al. 2012). Gcc is widely used for ground-based remote sensing in the visible spectrum to assess vegetation changes (Richardson et al. 2007, Zhao et al. 2012) and has demonstrated to be more robust to variations in weather illumination compared to alternatives (Sonnentag 2012).

$G_{CC}= DN_G/ DN_R+DN_G+DN_B$ {Equation 1}

NDVI/ MODIS (Satellite Based Remote Sensing)

To compare the relationship between proximal and satellite vegetation indices, MODIS land products was used to obtain NDVI metrics acquired from MOD13Q1 data via the Oak Ridge National Laboratory Distributed Active Archive Center (http://daac.ornl.gov). The acquisition region was centered over the camera locations for 5x5 pixel regions (~2.3x2.3km) and data was selected from March to September to reflect changes within the primary growing season. Only imagery on dates where quality assessment resulted in 100 percent approval were used. For comparison between NDVI and Gcc indices, five years of images were obtained, from 2011 to 2015 at PCC and RRC. Imagery at DRW spanned from 2013 to 2015, as ground based data was not available at this site until 2013. NDVI was calculated from the following equation. (NIR - Red) * (NIR + Red) (Rouse et al., 1974) {Equation 2}

Comparison of Gcc & NDVI

Visual analysis of graphs illustrating NDVI and Gcc over time in combination with summary statistics were used to characterize vegetation patterns. To compare trends of Gcc and NDVI explained by DOY, Z-scores (x-mean/standard deviation) were used in graphics to account for measurement differences. To assess the relationship between vegetation indices, linear models of Gcc explained by NDVI were first fit separated by site and year, and then

aggregated for an overall fit. The association was examined looking at coefficients of determination (R^2), standard error (SE), and standard deviation (σ).

Due to technical malfunctions, weather, and additional circumstances, complete daily observations were not maintained for the entire study period. Analyzing time-series data can be challenging due to the limitations of most statistical methods, including nonlinear trends, non-stationarity, and the necessity of continuous and regular temporal intervals of data collection. Therefore, missing daily values of ground-based vegetation dynamics (Gcc) were interpolated using the package 'zoo' (Zeileis et al. 2015). Similar interpolation of satellite-based measurements (NDVI) were attempted but upon visual assessment, failed to produce accurate representation of phenological metrics. Thus, the analysis comparing NDVI and Gcc was conducted on non-interpolated datasets, however characterization of vegetation phenology utilized an interpolated dataset of Gcc.

Using the interpolated dataset, vegetation dynamics were assessed with logistic models to fit Gcc as a function of time (Zhang et al. 2003). Phenometrics, or transitional dates of phenology, were determined by the rate of change in the curvature (Zhang et al. 2003). This included the onset of leaf growth (green-up), green leaf maturity (max. greenness), the decrease in photosynthesis and green leaf (senescence), and the range of days between green-up and senescence. Models were fit and phenometrics identified using the 'phenex' package (Lange and Doktor 2013) with a local threshold set to 0.1 (Lukasová et al. 2014). All statistical analyses were conducted in R 3.0.2 (R Development Core Team, 2012).

Results

Comparison of NDVI & Gcc

Overall, using digital time-lapse imagery, the ground-based vegetation index, Gcc, illustrated seasonal patterns with similar trends to NDVI at all study sites (Figure 6). Visual inspection of graphs of Gcc and NDVI over time showed a generally similar trend in vegetation with differences between sites and years. In 2013, 2014, and 2015, assessment of the temporal patterns of NDVI and Gcc at DRW were highly comparative. Ground-based data was not available at the DRW study location for 2011 and 2012, and thus was not assessed. At RRC and PCC in 2013 and 2014, Gcc and NDVI exhibited visually comparable temporal patterns, with a moderate difference observed in the extent of maximum greenness at PCC in 2014, and a slight difference in the slope of green up at RRC in 2014. In 2011, the observed patterns for Gcc and NDVI were similar at RRC, but temporal differences were evident at PCC. In 2012, results show inconsistencies at both RRC and PCC.

There was a significant positive linear associations found between Gcc and the satellite-based index, NDVI, as the overall R^2 which included all sites and years was 0.6876 ($p<0.05$, N=127). However, the strength varied between study locations and years (Figure 7). Gcc and NDVI exhibited positive linear relationships ($p<0.05$) at RRC in 2011, 2012, 2013, and 2014, at PCC in 2013 and 2014, and DRW in 2013, 2014, and 2015 (Table 1). The strongest associations between NDVI and Gcc were found at the DRW study site (R^2=0.947, R^2=0.682, R^2=0.969, $p<0.01$).

Vegetation Phenophase and Phenometrics from Time-lapse Imagery

Visual analysis of vegetation phenophase demonstrated overall similar patterns with differences observed in seasonal changes, between years, and among sites (Figure 9). During the entirety of the study period and inclusive of all sites, the mean DOY of vegetation green-up was DOY 113, vegetation reached a mean maximum greenness at DOY 196, senescence had a mean of DOY 291, and the range between green up and senescence had a mean of 176 days (Table 2). Average phenometrics during the study period for Gcc at RRC, the mean DOY during the study period for green-up was 119, the mean DOY for maximum greenness was 176, the mean DOY for senescence was 304, and the mean range of days was 181. At DRW, the mean DOY during the study period for green-up was 112, the mean DOY for maximum greenness was 223, the mean DOY for senescence was 288, and the mean range of days was 172. For Gcc phenometrics at PCC, the mean DOY during the study period for green-up was 107, the mean DOY for maximum greenness was 188, the mean DOY for senescence was 284, and the mean range of days was 175.

Phenometrics analyzed separately by year show green-up had a mean DOY of 123 in 2013, a mean DOY of 109 in 2014, and a mean DOY of 107 in 2015. The mean DOY maximum greenness was attained was 208 in 2013 and 183 in 2014. The mean DOY senescence began was 287 in 2013 with a range of 164 days and a mean DOY of 296 for senescence with a range of 187 days in 2014. In 2015, maximum greenness, senescence, and range of days were not calculated, as data was obtained only until spring, and thus, did not include the full phenophase.

Discussion

A foundational component in ecological interactions and processes at various spatio-temporal scales, assessment of vegetation changes relies on data acquisition at a multitude of temporal and spatial ranges. Ground based time-lapse camera systems were employed to acquire imagery at three locations and images were then used to calculate the vegetation index Gcc. The relationship between Gcc and the satellite-based index NDVI was assessed using linear models and compared between year and sites. Phenometrics were calculated from Gcc to characterize vegetation dynamics among site and years.

As mentioned previously, interpolation of missing values was attempted for satellite-based measurements, as statistical analysis of time-series data often relies on continuous datasets without missing values. However, the resulting temporal pattern and phenological metrics of the interpolated NDVI dataset were found to be visually inaccurate and erroneous compared to the temporal trends commonly associated with phenology research (Hufkens et al. 2012). This inaccuracy is likely attributed to the limited quantity of the acquired NDVI dataset, a result of the constraints imposed by the limited temporal frequency and atmospheric disturbances/cloud cover of satellite imagery during a narrow study duration, further emphasizing the necessity of repeated or continuous monitoring and data acquisition from additional methods.

Our results suggest differences between years and sites which may be an influence of multiple factors. The difference in satellite and ground-based characterization of vegetation phenophase may be attributed to the landscape surrounding the camera stations; at both a local and regional scale. At PCC, results show that for three of the five years, we failed to detect a significant relationship between NDVI and Gcc. Comparatively, at DRW, all three years were

highly correlated ($p<0.05$). This may be a result of the distance from the time-lapse camera system to the vegetation within the ROI. At PCC, the ROI encompassed an area of the image with a greater depth of field between the time-lapse camera system and the vegetation; about twice the distance than the depth of field at DRW. An accumulative effect with the oblique perspective of the camera system, which increases depth, this could have skewed pixel analysis as the calculation of Gcc relies on RGB color channels and is thus susceptible to lower pixel resolution, atmospheric disturbance, or slight camera movement. Furthermore, a difference in the landscape composition and species of vegetation within the frame of view may play a role in the differences in the association of NDVI and Gcc observed between sites; PCC was focused on a forested riparian zone adjacent to the river channel, while DRW was comprised of grassland next to a meandering slough.

In addition, discrepancies between NDVI and Gcc may be attributed to the difference in the scale of observation. For example, the landscape at PCC consists of sandpit lakes and agricultural fields. Thus, these attributes could alter the calculation of NDVI in relation to the metrics derived from time-lapse imagery. The selected region of interest used to calculate Gcc at PCC was centered on mostly riparian forest, and the difference in VI's may result from the heterogeneity of the ROI compared to the idiosyncrasies within the larger area of interest of the satellite imagery, or the attributed response of a specific vegetation type. In addition to monitoring systems at multiple scales, nuanced differences or similarities among data collection methods may provide further insight into scale-dependent environmental changes.

The discrepancies between years may be attributed to a combination of environmental factors. The mean DOY green-up began in 2013 was 123, approximately two weeks later than the

observed mean in 2014 (109) and 2015 (107). In 2013, the mean monthly temperature in the central Platte River Basin in April was 46°F, compared to 52°F in 2014, and 53°F in 2015 (https://www.ncdc.noaa.gov/). As local climatic conditions influence vegetation (Menzel 2000, Cleland et al. 2007), the lower temperature average in 2013 may have delayed vegetation green-up. In addition, although monthly averaged temperature for May and June were similar between years, vegetation phenophase exhibited a slow and minimally increasing growth in green-up. This is particularly true at PCC and DRW, where at its peak, vegetation greenness is substantially lower in 2013 compared to 2014. The phenometrics further this, as maximum greenness in 2013 had a mean DOY of 208, compared to 183 in 2014. This may be a result of limited water availability. In 2013, there was a total of 1.63in of rainfall in June and 1.39in in July, compared to 2014 which had a sum of 9.65in in June and 2.19in in July (https://www.ncdc.noaa.gov/).

Our results reinforce the findings of similar studies (Sonnentag et al. 2012, Hufkens et al. 2012) and demonstrate the value of ground based time-lapse imagery to assess landscape changes and obtain high temporal resolution data to examine vegetation dynamics. Albeit, there are numerous factors to take into consideration, including the depth of field, variations in the frame of view, and selecting methods of data acquisition which properly address the scale and scope of the research objective. With anticipated changes in global temperatures, rainfall, extreme events, and the timing of phenological events, monitoring ecosystems has become increasingly important (Parmesan & Yohe 2003). Digital time-lapse camera systems fill a data gap between human observation and satellite remote sensing, which allows for scaling-up of

phenological monitoring, and provides further insight into ecological functioning and understanding the impacts of climate change on ecosystem dynamics.

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Tables & Figures

Figure 1. Map of three study sites, Plum Creek Complex (PCC), Rowe River Channel (RRC), and Derr Restoration Wetland (DRW), within the central Platte River Basin of Nebraska.

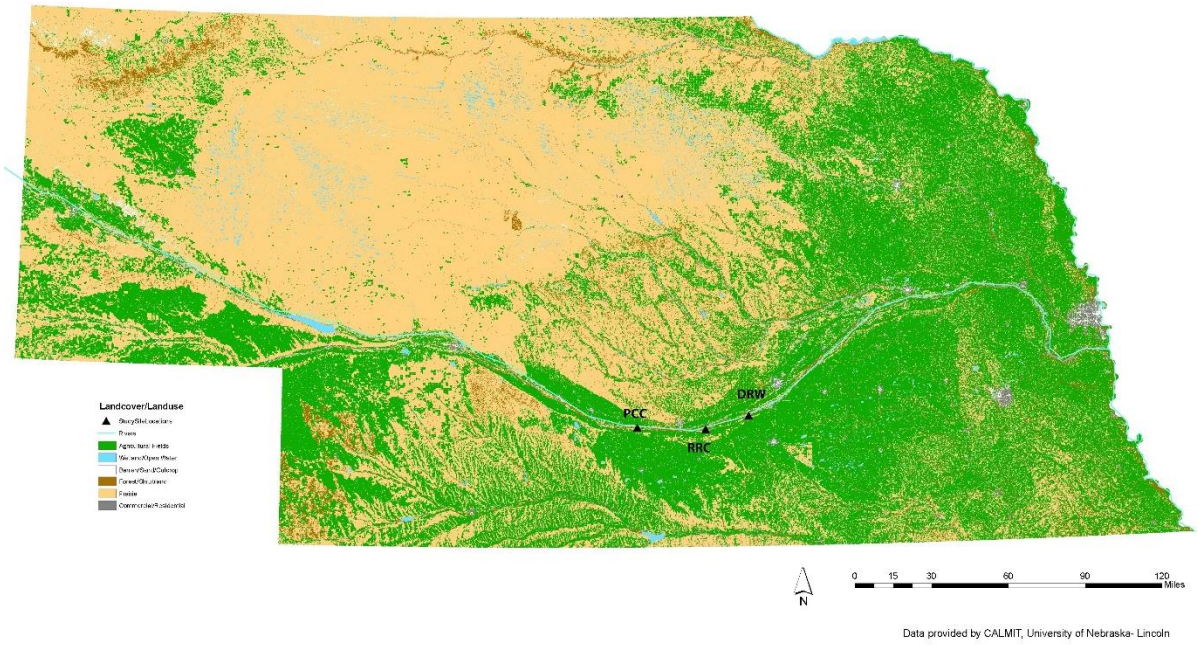


Figure 2. Digital time-lapse camera station with waterproof housing and solar panel.

Figure 3. Selected region of interest (ROI) used to calculate Green Chromatic Coordinate (Gcc) at Rowe River Channel (RRC) in the central Platte River Basin of Nebraska.

Figure 4. Selected region of interest (ROI) used to calculate Green Chromatic Coordinate (Gcc) at Derr Restoration Wetland (DRW) in the central Platte River Basin of Nebraska.

Figure 5. Selected region of interest (ROI) used to calculate Green Chromatic Coordinate (Gcc) at Plum Creek Complex (PCC) in the central Platte River Basin of Nebraska.

Figure 6. Line plots of satellite-based vegetation index NDVI and time-lapse camera vegetation index Gcc over time. Plots are of Z-scores to account for measurement differences and separated by site and year.

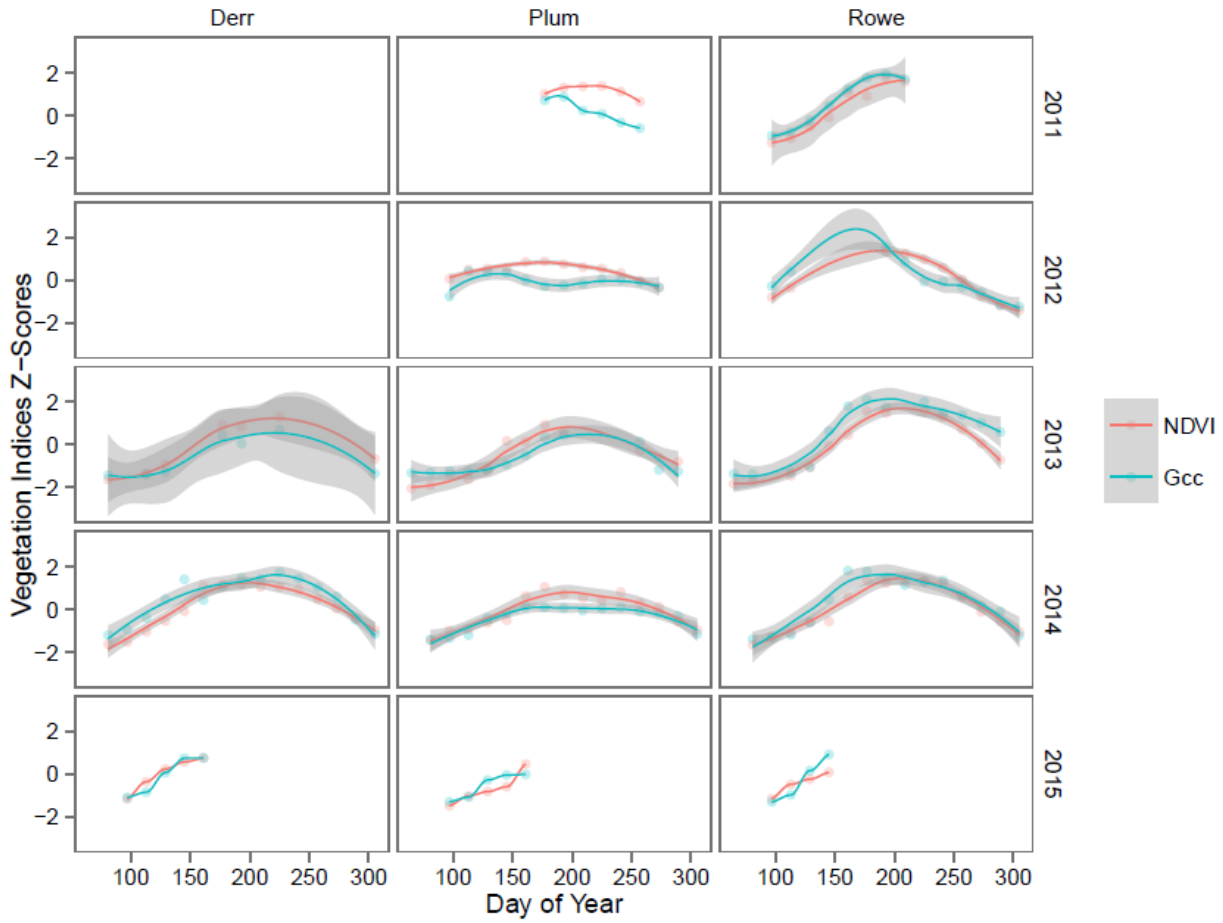


Table 1. R^2 of Normalized Difference Vegetation Index (NDVI) and Green Chromatic Coordinate (Gcc). Vegetation indices were calculated for 2013-2015 at Derr Restoration Wetland (DRW), and 2011-2015 at Plum Creek Complex (PCC), and Rowe River Channel (RRC).

Site	Year	adjusted R^2	standard error	p-value
Overall R^2		*0.686*	*0.018*	*<0.001*
DRW				
	2013	0.947	0.042	<0.001
	2014	0.682	0.086	<0.001
	2015	0.969	0.013	0.01
PCC				
	2011	0.389	0.038	0.155
	2012	-0.07	0.061	0.574
	2013	0.636	0.091	0.0019
	2014	0.765	0.059	<0.001
	2015	0.523	0.099	0.102
RRC				
	2011	0.931	0.046	<0.001
	2012	0.689	0.094	0.003
	2013	0.874	0.068	<0.001
	2014	0.844	0.066	<0.001
	2015	0.928	0.012	0.121

Figure 7. Plot of linear relationship between Green Chromatic Coordinate Vegetation Index (Gcc) and Normalized Difference Vegetation Index (NDVI) separated by site and year. Data was not available at Derr in 2011 and 2012.

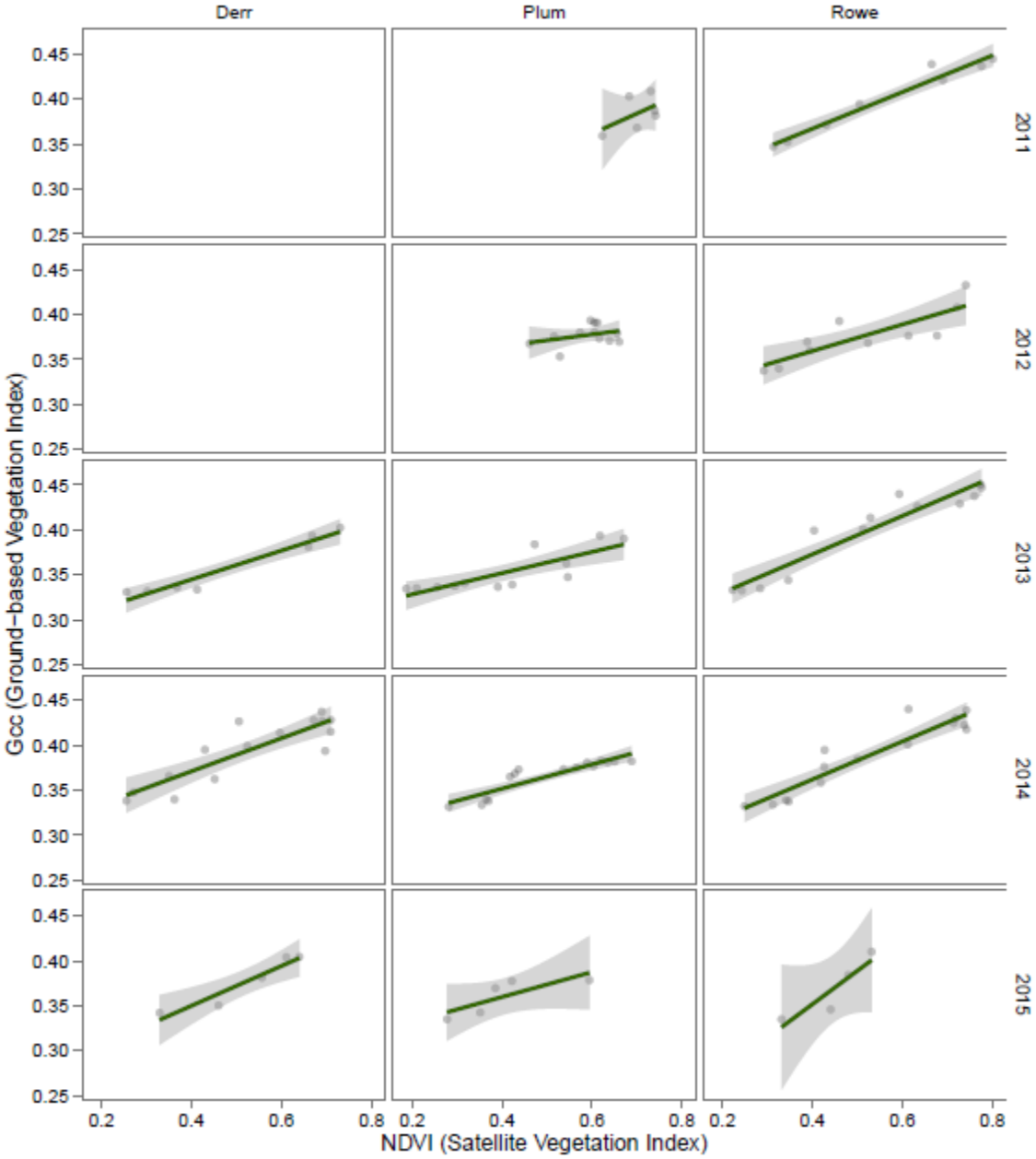


Table 2. Phenometrics from digital time-lapse imagery at RRC, DRW, and PCC study locations during 2013, 2014, and the spring of 2015.

	Greenup (DOY)	Max Green (DOY)	Senescence (DOY)	Range (days)
RRC				
2013	125	175	310	185
2014	120	177	297	177
2015	113	-	-	-
DRW				
2013	134	224	284	150
2014	98	221	291	193
2015	105	-	-	-
PCC				
2013	110	224	267	157
2014	108	152	300	192
2015	104	-	-	-

Figure 8. Vegetation phenometrics calculated by fitting a logistic model and identifying the rate of change in the curvature. First vertical line indicates first day of green up. Second vertical line is the first day of senescence.

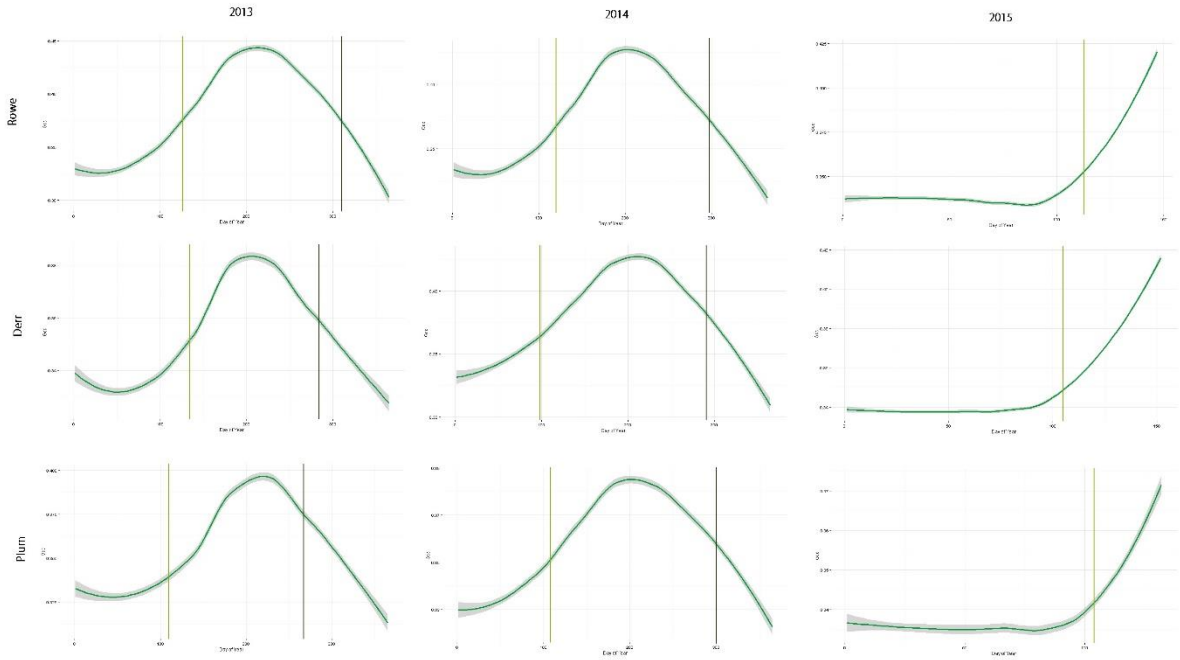
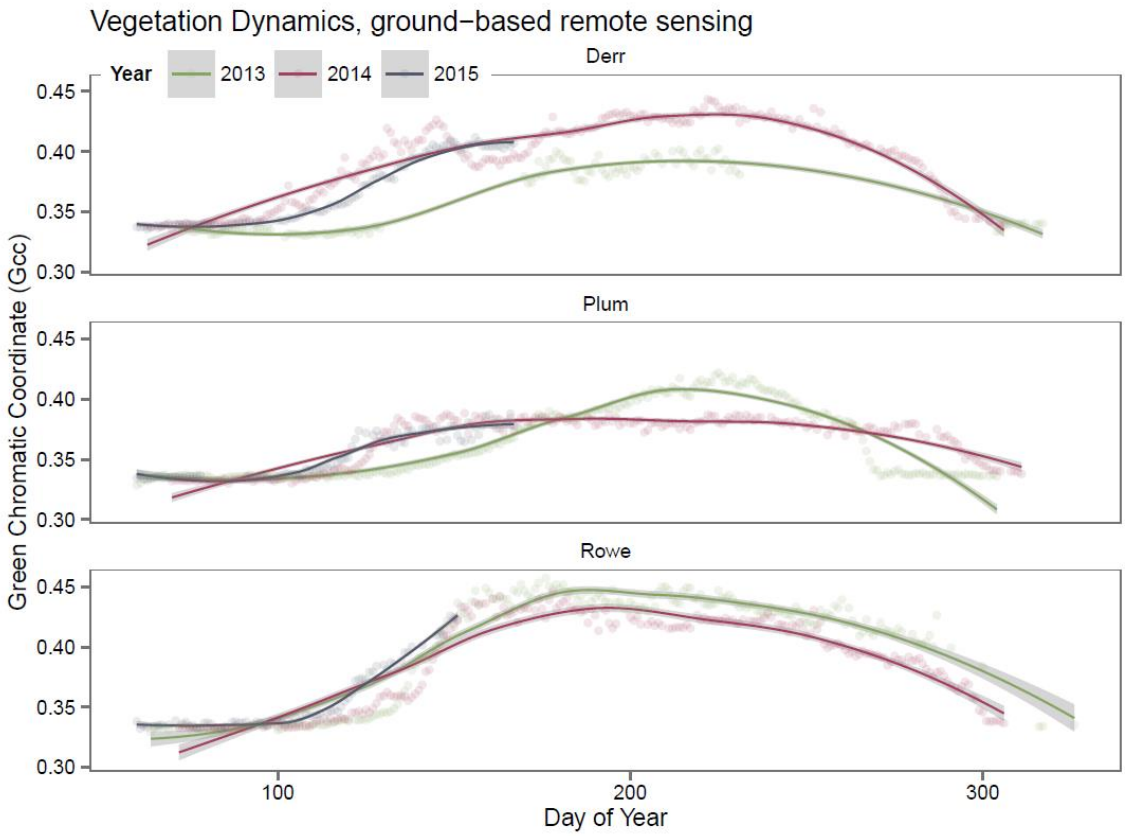


Figure 9. The characterization of vegetation phenophase, illustrated by the Green Chromatic Coordinate (Gcc) plotted by day of the year (DOY). Plots are separated by site and year is denoted by color.



CHAPTER 6. CONCLUSIONS & SYNTHESIS

This research explored the utility of time-lapse imagery to enhance understanding of natural systems through several ecological applications. Time-lapse imagery was concurrently employed as a tool to acquire data, as well as combined with data visualization to illustrate ecological dynamics. In addition, I examined how visual changes analyzed in the images, such as water-inundation and vegetation phenology, were associated with less visible occurrences acquired from additional monitoring, including water quality and bat activity.

Building upon foundational studies that utilize cameras in natural resource sciences (Webb 2010) and as ground-based sensors (Richardson et al. 2009, Sonnentag et al. 2012), this study contributes insight into integrated monitoring techniques by demonstrating how time-lapse imagery can simultaneously document multiple ecosystem attributes changing over time. It is largely an exploratory endeavor by means of methodological inquiry focused on multifunctional utility to dually document and depict ecological dynamics in the central Platte River Basin of Nebraska. This chapter looks to highlight main conclusions, address limitations and challenges, and provide recommendations for future research.

Chapter Conclusions

In the first chapter I reviewed scientific and communicative applications of time-lapse imagery to highlight the demonstrated capabilities, advantages, and to provide an overview of the technology. The wide range of disciplines and topics addressed in the review lay emphasis on the versatility and multifunctional proficiencies of time-lapse imagery as a technique.

In Chapter 2, I examined the potential to illustrate complex ecosystem changes by synthesizing time-lapse images with data visualization to create time-lapse data sequences. Imagery offered a visual context for connecting to a location, while data visualization provided content and empirical information to observe pattern and trend. Portrayal of both visually observable changes and elusive or invisible processes, dynamics, or occurrences was provided by combining mediums. This offered the potential to observe interconnected dynamics, such as increased water levels and changes in contaminants or seasonality and dissolved oxygen. Several examples demonstrate how time-lapse data sequences could be applied to both scientific and educational inquiries and overall, indicate potential applicability for a range of applications to enhancing understanding of natural systems.

In Chapter 3, the relationship between water-inundation levels derived from image-analysis, and water quality measurements at a restored wetland were analyzed using a combination of correlation analysis and AEM-RDA, a multivariate time-series modeling approach. Stream-gauge data, acquired from USGS stations opposed to image-analysis, and water-quality measurements were collected from a river channel site to examine the surface water fluctuations of the river system compared to the wetland. Water inundation at the wetland was positively associated ($p<0.05$) with nitrate (rho=0.63), DEA (rho=0.57), and dissolved oxygen (rho=0.56), as well as negatively associated with water temperature (rho=-0.72), suggesting that water quality fluctuates as a function of water level. Similarities in temporal patterns and deterministic water-quality parameters in the wetland and river channel, identified by AEM-RDA, were indicative of regional conditions driving fluctuations, such as climate or land-use. Differences in the significant AEM variables comprising the patterns may suggest a

divergence of morphological or physical attributes inherent of the individual sites, such as the large extent of connectivity among river systems compared to interconnectedness among wetlands and local terrestrial systems. Overall, utilizing time-lapse imagery in this capacity is of value because of its multifunctional abilities which were not restricted to only one sole purpose.

In Chapter 4, the relative activity of three species of bats were assessed in relation to several ecological variables, including vegetation phenology. Acoustic surveys recorded big brown, red bat, and evening bat activity during the spring and fall. Random forest and negative binomial generalized linear mixed models were used to model season and species-separated bat activity as a function of average nightly temperature, daily precipitation, average nightly wind speed, change in atmospheric pressure, moon illumination, site, year, and the green chromatic coordinate vegetation index, which was calculated from time-lapse imagery. Results were generally consistent between methods and found that vegetation phenology was a significant predictor of red and evening bat activity during both seasons, while big brown bat activity models showed more uncertainty in results and some association with vegetation during the fall. The significance of vegetation for red and evening bat activity, both migratory species, and the erratic response observed in resident big brown activity, suggests vegetation dynamics may offer potential insight for migratory bat species. Overall, this chapter hopefully acted as a stepping stone or catalyst to further investigate the relationship between ground-based vegetation dynamics and wildlife, particularly species that are elusive or challenging to study.

In Chapter 5, the green chromatic coordinate (Gcc) vegetation index was used to characterize vegetation phenology at three sites in the central Platte region. Phenometrics were calculated to assess the general and interannual phenology and compare between sites. The

Normalized Difference Vegetation Index (NDVI) was calculated from ~2.3x2.3km satellite imagery with a center point corresponding to a time-lapse camera station. Linear regression was used to model the relationship between Gcc and NDVI. Overall, Gcc and NDVI exhibited a strong association, however a difference in vegetation phenology was observed between sites and years. This is suggestive first of local site differences, for example the distance between the lens and vegetation analyzed for Gcc, as well as the variation at a landscape scale for calculating NDVI, such as the unintended inclusion of sandpits in the satellite imagery. Second, the observed differences in vegetation phenology among site and year may indicate a difference in environmental factors; precipitation levels varied between years while soil moisture and vegetation composition may differ among sites.

Limitations & Challenges

Several limitations of time-lapse imagery, as well as challenging factors to be cognizant of, were made apparent during this study. As observed with the change in error rate for image-analysis of water-inundation from over 20% in 2013, to less than 1% in 2015, maintaining a stable frame of view is a significant factor when utilizing images to acquire data. Movement within the frame can introduce variation within results and skew analysis, especially when batch processing many images. This is additionally true for producing aesthetically pleasing and compelling time-lapse video as an altered frame of view requires additional time and manipulation to stabilize the transitions between images into a seamless sequence. If a seamless transition isn’t capable with post-processing, movement within the frame of view results in a shaky and disjointed video, and can be a distraction from the overall message. A common

challenge when working with large amounts of data or files, there are technical, storage, and software limitations to using time-lapse imagery. Although very exciting and highly informative, I was at first overwhelmed by the immense collection of images offered by Platte Basin Timelapse. I found that sorting, finding, viewing, selecting, and copying high resolution photographs were a test of patience, time, and motivation to design an efficient process with well thought out goals. After a frustrating year of image management, Phocalstream, a program developed at the Raike School at UNL, was launched and significantly increased the efficiency in which I could select, sort, and download images. Although, storage capacity, older software, and computer systems are additional challenges or limitations for image processing. Moreover, scene illumination and weather variability is challenging when applying scripts or calculating vegetation indices. Standardizing image selection to a range of time with similar sun illumination as well as manual screening and vetting of images were beneficial for dealing with these limitations.

Future Considerations

This research was intended to hopefully act as a catalyst to incite further research into utilizations of time-lapse imagery. I found working with such an extensive catalog of PBT's photographs generated additional research and communicative inquiries for potential investigation. In regards to science communication, testing the efficacy of time-lapse images to communicate by designing an experiment or survey was a continuously emerging topic that is worth investigating further. In addition, measuring the ability of time-lapse imagery to improve understanding through a variety of applications, such as in a classroom setting versus in an immersive environment, or static vs dynamic, may be insightful. An intended direction that

wasn’t implemented due to time constraints, examining vegetation phenology across a latitudinal gradient throughout years may be of value in regards to phenological shifts and implications of climate change. Furthermore, assessing the associations between vegetation and wildlife dynamics across a range of latitudes may offer a more detailed account of migratory behavior and the relationship with vegetation phenology. An additional consideration for further research in regards to wildlife dynamics, it may be of interest to use time-lapse imagery to quantify changing water levels in an ephemeral wetland with co-located surveys of wildlife, particularly in regions where water-stress may be a limiting or determinant factor driving behavior and occurrence.

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