Ecological Restoration of an Oak Woodland in Kansas Informed with Remote Sensing of Vegetation Dynamics

by

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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Horticulture and Natural Resources
College of Agriculture

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Abstract

Recurrent, landscape-level fires played an integral part in the development and persistence of eastern oak (*Quercus spp.*) forests of the United States. These periodic surface fires helped secure a competitive position for oaks in the regeneration pool by maintaining a desirable species composition and forest structure. This historical fire regime was altered with the European settlement of North America, and fire suppression within forestlands became a standard practice since 1930s. With decades of fire suppression, mature oak-dominated woodlands have widely converted to shade-tolerant tree species. Prescribed fire has successfully been used to enhance oak regeneration in eastern forests. However, oak woodland restoration within the forest-prairie ecotone of the Central plains has not been systematically studied. Fuel beds under shade-tolerant species are often less conducive to fire. Therefore, monitoring fuel loading (FL) and its changes are essential to inform management decisions in an oak regeneration project. Rapid expansion of eastern redcedar (*Juniperus virginiana*/ERC) is another ecological issue faced by land managers throughout North America's midcontinent forest-prairie ecotone. Hence, it is worthy to monitor ERC expansion and effects on deciduous forests, to inform oak ecosystem restoration interventions within this region. Therefore, the main objectives of this dissertation were three-fold: (1) understand the effects of prescribed burning and mechanical thinning to encourage oak regeneration; (2) investigate the initial effects of an oak regeneration effort with prescribed fire and mechanical thinning on FL; and (3) monitor the spatio-temporal dynamics of ERC expansion in the forest-prairie ecotone of Kansas, and understand its effects on deciduous forests. The first two studies were conducted on a 90-acre oak dominated woodland, north of Manhattan, Kansas. The experimental design was a 2 (burn) x 2 (thin) factorial in a repeated measures design. The design structure allowed four treatment

combinations: burn only (B), thin only (T), burn and thin combined (BT), and a control (C). Burning and thinning treatments were administered in spring 2015. Changes in the FL estimates after the burn treatment revealed that the BT treatment combination consumed more fuel and burned more intensely compared to the B treatment. This observation was reflected in vegetation responses. The thinning reduced the canopy cover significantly, but under enhanced light environments, both oaks and competitive species thrived when no burn was incorporated. In contrast, burn treatments controlled the competitive vegetation. Hence, the most promising results were obtained when both fire and thinning were utilized.

The remote sensing study documented the expansion of ERC in three areas of eastern Kansas over 30 years. The use of multi-seasonal layer-stacks with a Support Vector Machines (SVM) supervised classification was found to be the most effective approach to map ERC distribution. Total ERC cover increased by more than 6000 acres in all three study areas investigated in this study between 1986 and 2017. Much of the ERC expansion was into deciduous woodlands. Therefore, ERC control measures should be incorporated into oak woodland restoration efforts within the forest-prairie ecotone of Kansas.

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Table of Contents

List of Figures xii

List of Tables xv

Acknowledgements xvii

Dedication xix

Chapter 1 - Introduction 1

Background and Rational 1

Organization of the dissertation 3

References 4

Chapter 2 - Literature Review 5

Historical development of the eastern oak forests 5

Fire suppression and the oak regeneration issue 6

Natural succession and the concept of climax forest 8

Predation 10

Social constraints 10

Re-introducing fire into the forests 11

Positive effects of fire in forestlands 11

Negative effects of fire in forestlands 14

Prescribed fire as a silvicultural practice to restore oak ecosystems 15

Regeneration response 16

Site quality and fire intensity 17

Fire frequency 18

Thinning 18

Limitations of introducing a fire regime into a mature oak forest ... 19
Prescribed fire use in natural resource management ... 21
Prescribed fire use in Kansas: Preserving the integrity of the Flint Hills ... 23
Eastern redcedar encroachment in the forest-prairie ecotone of Kansas ... 26
Remote sensing applications in natural forest management ... 28
Studying vegetation dynamics and spatio-temporal analysis ... 28
Small Unmanned Aircraft Systems (sUAS) applications in forestry ... 29
References ... 32
Chapter 3 - Ecological Restoration of an Oak Woodland within the Forest-Prairie Ecotone of Kansas ... 39
Abstract ... 40
Introduction ... 41
Methods ... 44
Study site and experimental design ... 44
Treatments ... 45
Data collection ... 47
Data processing and statistical analyses ... 48
Results ... 49
Vegetation structure and composition ... 49
Seedling response to burn ... 52
Canopy and understory vegetation cover ... 53
Discussion ... 53
References ... 56

Chapter 4 - Prescribed Fire and Mechanical Thinning Effects on Fuel Loading in an Oak Dominated Woodland in the Forest-Prairie Ecotone of Kansas 70

Abstract 71

Introduction 72

Methods 74

Study site and experimental design 74

Treatments 75

Data collection 75

Data processing and statistical analyses 77

Results 79

Initial burn treatment effects on fuel loading 79

Fire effects on understory vegetation and tree/ sapling fire scars 82

Fuel loading recovery 83

Discussion 84

References 88

Chapter 5 - Monitoring the Effects of Eastern Redcedar Expansion on Deciduous Forests within the Forest-Prairie Ecotone of Kansas using Multi-temporal Landsat Images 101

Abstract 102

Introduction 103

Method 107

Study area and dataset 107

Data 108

Characterizing an effective classification approach 109

K-means clustering algorithm 109
ISODATA 110
Maximum likelihood 111
Support vector machines (SVM) 111
Multi-seasonal layer stacking with SVM 112
Composite/multi-temporal image analysis with SVM 113
Accuracy assessment 113
Assessing ERC expansion between 1986-2017 114
Accuracy assessment and area estimation 114
Results 115
Selecting the most effective classification approach 115
ERC dynamics within the three study regions 117
Tuttle Creek Reservoir 117
Perry Lake 118
Bourbon County North 119
Discussion 120
References 124
Appendix A - Field Work Photos 164
Appendix B - Inventory Sheets 181
Appendix C - Site Index Curve 187
Appendix D - Stocking Diagram 188
Appendix E - Workflows for Chapter 5 189

List of Figures

Figure 2-1. Ecoregions of the United States: The region corresponding to 251 and 255 together represents the forest-prairie transitional region (Bailey, 1994). 31

Figure 3-1. Study Area delineated into 12 compartments. Eastern redcedar areas are represented in darker color 58

Figure 3-2. Permanent Data Collection Points 59

Figure 3-3. Permanent data collection plot structure 60

Figure 3-4. Trees per acre (left) and Basal Area Per acre (right) for the a) Total, b) Oaks c) Eastern redcedar 61

Figure 3-5. Saplings per acre (left) and Sapling Basal Area Per acre (right) for a) Total, b) Oaks c) American Elm d) Eastern redcedar 62

Figure 3-6. Seedlings per acre for a) Total, b) Oaks c) Eastern redbud d) Eastern redcedar 63

Figure 3-7. Tagged seedling responses 64

Figure 4-1. Study area delineated into 12 compartments 90

Figure 4-2. Permanent data collection points (circular plots) 91

Figure 4-3. FIREMON sampling plane layout (1 transect) for FL estimation (Lutes et al., 2006) 92

Figure 4-4. Quadrat based (left) and transect based (right) estimates on initial burn effects on litter, duff and total FL measured by the two methods 93

Figure 4-5. Quadrat based (left) and transect based (right) estimates on Fuel Load (FL) recovery with regard to litter, duff and total FL measured by the two methods 94

Figure 5-1. Ecoregions of the United States: The region corresponded by 251 (prairie parkland province - temperate) and 255 (prairie parkland province – subtropical) together represents the forest-prairie transitional region (Bailey, 1994).. 127

Figure 5-2. The forest-prairie ecotone of Kansas is represented by yellow county lines. Three Landsat OLI images: scene path 28/ row 33 (21st January 2017), path 27/ row 33 (03rd March 2017) and path 27/ row 34 (03rd March 2017) covers majority of the area. Images are displayed in a false color scheme: Near-infrared, red and green as RGB. 128

Figure 5-3. Study Areas 1). Tuttle Creek Reservoir, 2). Perry Lake, and 3). Bourbon County North 129

Figure 5-4. False color composite of the study region surrounding the Tuttle Creek reservoir in 1986 (left) and 2017 (right). Eastern redcedar vegetation is represented in maroon, in this dormant season image 130

Figure 5-5. K-means clustering classification products.. 131

Figure 5-6. ISODATA clustering classification products.. 132

Figure 5-7. Maximum Likelihood classification products... 133

Figure 5-8. Support Vector Machine (SVM) classification products 134

Figure 5-9. Multi-temporal SVM classification products.. 135

Figure 5-10. Multi-temporal SVM (improved) classification products.................................... 136

Figure 5-11. Composite image classification with SVM... 137

Figure 5-12. Study area 1: Tuttle Creek reservoir. A) 1986 Landsat TM image, B) 2017 Landsat OLI image, C) 1986 classified image, and D) 2017 classified image 138

Figure 5-13. Change map (1986 to 2017) - Tuttle Creek reservoir 139

Figure 5-14. Study area 2: Perry Lake. A) 1986 Landsat TM image, B) 2017 Landsat OLI image, C) 1986 classified image, and D) 2017 classified image 140

Figure 5-15. Change map (1986 to 2017) - Perry Lake 141

Figure 5-16. Study Area 3: Bourbon County North. A) 1986 Landsat TM image, B) 2017 Landsat OLI image, C) 1986 classified image, and D) 2017 classified image 142

Figure 5-17. Change map (1986 to 2017) – Bourbon County north 143

Figure 5-18. Total ERC encroachment between 1986 to 2017 for three study areas, broken by conversion of deciduous forests and non-forest classes to ERC 144

List of Tables

Table 3-1. Species composition of the entire study area at pre-treatment inventory.................... 65

Table 3-2. Pre-and Post-comparison of TPA and BA/acre.. 66

Table 3-3. Pre and Post comparison of Saplings per acre and Sapling Basal area 67

Table 3-4. Pre-and Post-comparison of Seedlings per acre 68

Table 3-5. Canopy cover and understory vegetation measurements 69

Table 4-1. Pre-and Post-burn fuel dry weights - Quadrat sampling 95

Table 4-2. Pre-and Post-burn fuel loading - Transect sampling 96

Table 4-3. Fire scar analysis 97

Table 4-4. Understory vegetation dry weights.. 98

Table 4-5. Fuel load recovery - Quadrat sampling 99

Table 4-6. Fuel load recovery - Transect sampling 100

Table 5-1. Landsat scenes used in the study 145

Table 5-2. Class Score value assigned to each classified image.. 146

Table 5-3. Reclassification of change map 147

Table 5-4. Error matrix - K-means clustering algorithm 148

Table 5-5. Error matrix - ISODATA classification 149

Table 5-6. Error matrix - Maximum likelihood classification... 150

Table 5-7. Error matrix -Support Vector Machines (SVM) 151

Table 5-8. Error matrix - Multi-seasonal SVM classification 152

Table 5-9. Error matrix - Multi-seasonal SVM (improved) 153

Table 5-10. Error matrix of sample counts - Tuttle Creek Reservoir Change Map.................... 154

Table 5-11. Error matrix with estimated proportions of area - Tuttle Creek reservoir............... 155

Table 5-12. Area estimations with 95% Confidence Intervals - Tuttle Creek reservoir............ 156

Table 5-13. Error matrix of sample counts - Perry lake change map 157

Table 5-14. Error matrix with estimated proportions of area – Perry lake 158

Table 5-15. Area estimations with 95% Confidence Intervals - Perry lake............................... 159

Table 5-16. Error matrix of sample counts – Bourbon County North change map.................... 160

Table 5-17. Error matrix with estimated proportions of area – Bourbon County North 161

Table 5-18. Area estimations with 95% Confidence Intervals - Bourbon County North........... 162

Table 5-19. Thirty Year ERC change within the three study areas 163

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Dedication

To my parents, brothers and sister

for their endless love, support and encouragement throughout my life

To my loving wife, *Pavithra*

for her unconditional love and support

To my daughter, *Methuli*

for being my inspiration..

Chapter 1 - Introduction

Background and Rational

As evident through paleo-ecological and dendrochronological studies, recurrent landscape level surface fires played an integral part in the development and persistence of the eastern oak (*Quercus spp.*) forests of the United States (Abrams, 2016; Brose et al., 2014). Being intermediate in shade-tolerance, oaks maintained a competitive position in the regeneration pool when benefitted by periodic fires. However, this historic fire regime was altered with the European settlement of North America. Since the 1930's, fire suppression has been a standard practice in forest management, allowing forests to develop closed canopies with dense mid-stories of shade-tolerant species. This caused the micro-environment within the forests to change substantially, as cooling, dampening, and shading (mesophication) of the understories were observed (Abrams, 2016; Nowacki and Abrams, 2008). The gradual conversion of oak dominated woodlands to shade-tolerant species was documented across the eastern United States (Dey, 2014; Nowacki and Abrams, 2008).

Many silvicultural practices including prescribed fire and mechanical thinning have been investigated for effectiveness in restoring oak forests in the eastern United States (Brose, 2014; Dey et al., 2016). However, oak woodland restoration within the forest-prairie ecotone of Kansas has not being systematically studied. Therefore, this research project was initiated in 2014 as a long-term research study investigating the effect of restorative practices in an oak dominated woodland within the forest-prairie ecotone of Kansas, using prescribed fire and mechanical thinning.

This dissertation consists of three studies related to the above project. The first study in chapter three investigates the direct effects of prescribed fire and mechanical thinning on vegetation structure and composition. Mesophication of oak forests results in the growth and abundance of shade-tolerant, fire-sensitive species. Fuel beds under these species are often less conducive to fire. Therefore, the success of any restoration effort involving prescribed fire depends on fuel loading and associated fire behavior. Hence, the second study in chapter four investigates the effects of prescribed fire and mechanical thinning on fuel loading. Both these studies were conducted on a 90-acre oak dominated woodland, north of Manhattan, Kansas owned by the Department of Horticulture and Natural Resources, Kansas State University. Fire has been excluded from this woodland for many decades. Therefore, it is unrealistic to expect a complete compositional and structural change with one treatment. Continuous management for 10 or more years may be required to observe desired changes. Therefore, as mentioned earlier, the two studies in this dissertation encompasses the initial three years of what will be a long-term research venture.

The third study in chapter five, employs a remote sensing approach to study vegetation dynamics throughout the forest-prairie ecotone of Kansas. The study focuses on Eastern redcedar (*Juniperus virginiana*/ERC), an evergreen tree species exhibiting rapid expansion rates. It is encroaching at an alarming rate throughout North America's midcontinent forest-prairie ecotone, causing significant impacts on surrounding grassland and forest ecosystems (DeSantis et al., 2011; Meneguzzo and Liknes, 2015; Williams et al., 2013). Therefore, this study investigates spatio-temporal dynamics of ERC expansion over a 30-year period within eastern Kansas and its impact on deciduous forests using Landsat satellite imagery. As part of the study, an effective image classification approach to map ERC distribution is characterized.

Organization of the dissertation

The dissertation contain five chapters as follows;

Chapter 1: Introduction

Chapter 2: Literature Review

Chapter 3: Ecological Restoration of an Oak Woodland within the Forest-Prairie Ecotone of Kansas

Chapter 4: Prescribed Fire and Mechanical Thinning Effects on Fuel Loading in an Oak Dominated Woodland in the Forest-Prairie Ecotone of Kansas

Chapter 5: Monitoring the Impacts of Eastern Redcedar Expansion on Deciduous Forests within the Forest-Prairie Ecotone of Kansas using Multi-temporal Landsat Images

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Chapter 2 - Literature Review

Historical development of the eastern oak forests

Paleoecology and dendrochronology studies provide vital insights into the historical development of oak (*Quercus spp.)* ecosystems in North America. By 9000 to 7000 years ago, oaks in eastern United States forests started to increase in abundance at a staggering pace (Abrams, 2016). Witness tree studies confirm that by the time of European settlement of North America, oaks were an abundant species. Pre-settlement vegetation types in the eastern United States were characteristically pyrogenic in nature; maintained by recurrent low- to mixed-intensity fire regimes (Frost, 1998; Nowacki and Abrams, 2008). These historical fire regimes characterized by recurrent, landscape-level fires were pivotal for the development and persistence of the eastern oak and pine forests of the United States in open "park-like" savannahs (Nowacki and Abrams, 2008; Abrams, 2016). Oaks benefited from such periodic fires which secured them a competitive position in the regeneration pool (Brose et al., 2014). Native Americans actively managed these lands with fire. After European settlement, this historic fire regime was altered (Guyette et al., 2006).

Industrialization of the forestry sector accommodated the huge timber demand between 1850 and 1920, with the logging of millions of acres of forests in the eastern United States. Logging debris left behind after this "clear-cut" era triggered the onset of huge catastrophic wildfires (Keyser et al., 2016; Ryan et al., 2013). The large-scale clear-cutting and wildfires of the early 1900s was followed by introduction of an exotic disease; chestnut blight fungus (*Cryphonectria parasitica*) which became an epidemic leading to an astounding impact on the eastern forests. Nearly 100% of the American chestnut trees (*Castanea dentata*), a major component of the forests at that time, died (Keyser et al., 2016). However, opportunistic tree species such as oaks and hickories expanded to fill in the chestnut niche and thereby increased their percent composition of eastern forests (Keyser et al., 2016).

Upland oak sites in Kansas belong to the "Oak Savannah and Prairie region", one of the four primary oak growing regions in the eastern United States (Oswalt and Olson, 2016). This region constitutes the forest-prairie transition region between the heavily forested eastern United States and the grasslands to the west. Therefore, the natural vegetation in this region is a mix of both forests and grasslands (Johnson et al., 2009; Oswalt and Olson, 2016). Compared to upland oak sites in the eastern United States, these oak sites typically have a sparser canopy cover and less dense herbaceous understory.

Fire suppression and the oak regeneration issue

Exhaustive timber felling, pest and disease outbreaks, and devastating forest fires in early 1900s steered a conservation movement within federal and state land management agencies. As a result, since the 1930s, fire prevention and suppression became a standard practice among federal and state agencies, a policy which was implemented with interagency cooperation (Abrams, 2016; Keyser et al., 2016; Nowacki and Abrams, 2008; Pyne, 1982).

Decades of fire suppression altered the stand structure and composition profoundly where fire-adapted species such as oaks were gradually replaced by shade-tolerant, fire sensitive species in eastern forests (Nowacki and Abrams, 2008). Similarly, the changed fire regimes altered the species composition and vegetation structure in the mid-continent forest-prairie ecotone of the United States as well (Briggs et al., 2002b; DeSantis et al., 2011). Oak savannah woodlands of this region are one of the greatly imperiled ecosystems in North America. Agriculture has replaced fire as the restrictive agent, marginalizing woodlands/ forests to riparian zones and areas with steep slopes that are not suitable for agriculture (Johnson et al., 2009; Oswalt and Olson, 2016).

Many factors contribute to a lack of oak regeneration, such as a shaded understory, understory competition, high seed predation and deer browsing. However, stringent fire suppression policies adopted by federal agencies, supported by a successful campaign to change social perception (Smokey Bear) towards fire in forests were a major cause of the current oak regeneration problem (Brose et al., 2013; Brose et al., 2014).

Oak is known to be intermediate in shade-tolerance, where its seedlings can survive in a partially shaded environment with slow growth rates. However, if low light levels persist for a longer period, they eventually die (Stringer, 2016). Periodic fires in these landscapes helped maintain a higher level of light reaching the forest floor through understory, mid-story and some over-story mortality. With decades of fire suppression, most of these forests have developed closed canopies with dense mid and understories.

Being intermediate in shade-tolerance, oaks must compete with both shade-intolerant and shade-tolerant species under differing light conditions. Forests that developed in a fire-free environment for many decades are characterized by shaded understories as explained above. Under these conditions, oaks will be outcompeted by shade-tolerant, mesophytic species such as sugar maple, red maple and American beech (in the eastern United States), and will persist without much growth (Schweitzer et al., 2016; Stringer, 2016). With limited sunlight, oaks are unable to build large root reserves and; if conditions persist, they will eventually die. In contrast, natural disturbances such as ice storms, wind damage or natural tree fall can suddenly increase light levels. At the forest floor, all forest species will respond to the increased light, especially shade-intolerant fast-growing species such as yellow poplar. Yellow poplar is a strong competitor of oaks exhibiting a shoot centric growth, as contrasted with oaks' root-centric growth pattern (Schweitzer et al., 2016; Stringer, 2016).

Natural succession and the concept of climax forest

Existence of its own seedlings under a given species, depends on its own characteristics such as level of tolerance to shade. These characteristics would determine how competitive a species is and where it belongs along the successional trajectory for that environment. Seedlings of pioneer species which thrive after disturbances that increase sun-light, are shade-intolerant. Therefore, for early- to mid-successional shade-intolerant species, it is common to have fewer seedlings with increased shade. In contrast, seedling growth in the shade of larger trees is abundant for shade-tolerant species. Intermediately shade-tolerant species such as oak, prefer intermediate levels of light.

The concept of "climax forest" is congruent with the theory of succession which is one of the highly debated theoretical explanations in ecology (Christensen, 2014; Kimmins, 2004). Simply, succession refers to the process of change where biotic communities of an area replace each other over time through the alterations they impose on the physical environment where they live. The fundamental concept of succession is a progressive, directional/ deterministic change in communities (sere) which ultimately leads to a final seral stage which is the most stable, self-perpetuating community (climax community) characteristic of the region (Kimmins, 2004). Within this explanation, "a climax forest" would be the forest community that represents the final stage of natural succession of an environment. This community represents the most stable composition of species for that regional climate. The classic climax species can successfully reproduce under their own shade, and can persist for a very long period. However, the theory of succession and the concept of climax community is contested within the scientific community.

Christensen (2014) reviewed the development of concepts of forest succession and their relevance to ecosystem restoration in North America. He concluded that; *"no single unifying mechanism for successional change exists, successional trajectories are highly varying and rarely deterministic, and that succession has no specific endpoint (climax)"*. The main argument against the concept "climax" is: since successional trajectories are highly variable and cyclic, when ecosystems undergo changes following a disturbance they become more prone to another disturbance over time (Christensen, 2014). Therefore, a conclusion can be made that the successional process is a cyclic process which can lead to a stable climax community over time, but it won't be the endpoint. With major disturbances, the succession process re-sets to an earlier successional stage.

In many ecosystems in the eastern United States, oaks are not considered to be the climax forest, but are considered to be a mid-successional species (Burhans et al., 2016). Savannahs typically have 10-30% canopy cover, while woodlands having 40-60%, sometimes up to 80% cover (Keyser et al., 2016). An open canopy, along with a well-developed shrub and young tree component, are the characteristic features of early- to mid-successional habitats (Greenberg et al., 2011), that favor oak regeneration and recruitment. However, these systems are converting to increased canopy cover and especially midstory and understory thickening with mesophytic species. The situation is worst on medium to high-quality sites, where shade-tolerant species grow vigorously and further suppress oak regeneration (Stringer, 2016). Many of the oak-dominated woodlands in the forest-prairie transitional region of Kansas are in steep slopes with low-to medium site quality. Hence, the situation is little better than high-quality oak sites in the eastern United States.

One of the main arguments against the concept of "climax" forest in Christensen's (2014), was that the term "climax" misleadingly implies that climax state is always the "best" compared to all other seral stages. However, compared to climax state, mid-successional stages often have a higher species diversity, maintain more wildlife, produce more valuable timber and provide many other benefits. Oak-dominated ecosystems are a good example, as they provide many ecological, economical and aesthetic benefits compared to the mesophytic species that replace them (Brose et al., 2014).

Predation

Seed predation is another major limiting factor on successful oak regeneration. Acorn weevils (Coleoptera: Curculionidae), gall wasps (Hymenoptera: Cynipidea) and acorn moths (Lepidopter: Oleuthreutidae) cause significant pre-dispersal mortality of oak acorns, hindering regeneration (Kellner et al., 2014; Lombardo and McCarthy, 2009). Lombardo and McCarthy (2009) showed that the germination percentage of red oak acorns (*Quercus rubra* L.) was 26% after weevil infestation, compared to 86% for sound acorns. White-tailed deer *(Odocoileus virginianus)* feed heavily on oak acorns, seedlings and saplings. Deer especially browse on new sprouts in spring and summer. Therefore, high deer densities are detrimental for oak regeneration (deCalesta et al., 2016). Historically, white-tail deer densities in eastern forests ranged from 2-4 deer/km^2, compared to a current density of >10 deer/km^2 with some regions reporting as having more than 17 deer/km^2 (Dey, 2014). This large deer population is capable of causing complete failure of oak regeneration (Dey, 2014).

Social constraints

In the midst of all the ecological and silvicultural challenges lies a social constraint contributing towards oak regeneration failure (Dey, 2014). Private landowners own a significant portion of the eastern forests. Therefore, their understanding and perception towards the current regeneration problem and management implications is vital. Dey (2014) states that most landowners aren't concerned with the current oak regeneration problem which is a serious issue and may lead to oak forests to decline regionally. Many landowners are skeptical about introducing prescribed fire into their forest lands, thus precluding its use in enhancing oak regeneration.

Re-introducing fire into the forests

Positive effects of fire in forestlands

Many ecologists argue that eliminating fire-mediated disturbance and allowing succession to run its course would result in "unnatural forests" and therefore requires science-based management practices to mimic the natural disturbance process (Burhans et al., 2016). The re-introduction of fire and other disturbances would help promote oak regeneration and restore eastern oak ecosystems. However, controversy still exists on the use of fire in forestlands, where some argue that nature should be allowed to take its course in repairing these damaged ecosystems (Arno and Fiedler, 2005). Therefore, it is important to understand the positive and negative effects of prescribed burning and allowing wildfire to burn in forestlands.

As explained above, exclusion of fire for many decades, which was formerly a natural force in these ecosystems profoundly altered the structure and composition of the forestlands (Nowacki and Abrams, 2008). In some regions of eastern oak dominated woodlands, "mesophication" (cooling, dampening and shading) of forestlands is observed (Nowacki and Abrams, 2008). The xerophytic species such as oaks and hickories are gradually being replaced by mesophytic species which are less fire-tolerant, and they produce less flammable litter. The overall effect of this process is that these ecosystems are becoming less conducive to fire (Brose et al., 2014; Hammond and Varner, 2016).

Much research has been conducted on restoring these forestlands, and prescribed burning has been identified as an effective management practice that can be used to mimic the historical disturbance regime (Brose et al., 2014; Dey et al., 2016). Prescribed fire is the use of fire in a knowledgeable manner to achieve predetermined management objectives and is conducted under favorable environmental conditions which usually allow the fire to be contained within a specified area (Harper and Keyser, 2016).

Oak savannah and woodlands are characterized by sparser tree canopies and rich herbaceous understories (Johnson et al., 2009; Oswalt and Olson, 2016). These are the typical oak ecosystems found in the forest-prairie ecotone of Kansas. Use of prescribed fires in these woodlands will maintain a healthy, nutritious herbaceous understory which would attract more wildlife populations (Abrams, 2016). New vegetation growing after fires is more palatable and high in nutrients that favors grazing and browsing animals (Harper and Keyser, 2016). Prescribed burning and low-intensity wildfires also benefit these ecosystems by disposing of downed woody debris, slash and the litter layer which favor more seedling establishment and acorn germination. Fire also speeds up nutrient cycling and assists in the elimination of soil-borne pathogens and diseases (Williams, 2000).

Wildfire can occur under similar conditions as for prescribed fire, but can also occur under extreme conditions resulting in less desirable results. However, Harper and Keyser (2016), argue that wildfire effects are not always negative; rather, in many instances the overall effect is positive. This is often valid with eastern forests that are less conducive to fire due to mesophication. Therefore, wildfires in these forests often are slow-moving with flames of less than one-foot-tall (Harper and Keyser, 2016). Fire effects can be strongly attributed to fire intensity, timing, and frequency (Harper and Keyser, 2016). Hence, the same positive effect of prescribed fire in restoring upland oak ecosystems can be obtained by allowing low intensity wildfires to burn.

In contrast to eastern forests, in most of the western forests, fire suppression has led to accumulation of combustible fuels over time, making them extremely vulnerable to catastrophic wildfires (Arno and Fiedler, 2005). In addition, human activities such as land fragmentation, agriculture, industrial forest plantations, building of residential and recreational areas has complicated the natural setting of these landscapes. Along with the effect of other indirect anthropogenic effects such as climate change and introduction of invasive species, the natural successional trajectories of these ecosystems have been altered, which makes restoration efforts challenging (Christensen, 2014).

Fire can also be used as a fuel reduction treatment, especially in western forests, making them less vulnerable to extreme wildfires. Recurrent, low intensity wildfires would benefit these forests as well by reducing build-up of combustible fuels on the ground (Williams, 2000). This reduced wildfire risk has a positive effect in protecting the surrounding properties and residential areas from catastrophic wildfires. Carbon sequestration by forests has received much attention recently as a climate change mitigation option (Wiedinmyer and Hurteau, 2010). However, catastrophic wildfires release large quantities of carbon to the atmosphere. Hence, prescribed fire can be used to reduce wildfire risk and thereby reduce excessive carbon emissions (Wiedinmyer and Hurteau, 2010).

Negative effects of fire in forestlands

Prescribed burning and wildfires can also be very detrimental to the forest, by harming recently fallen acorns, seeds, and by top-killing seedlings. For oaks, if these seedlings have not developed large root stocks they will not be able to recover. When fire intensities are high, they can scorch mature trees, reducing their timber value (Harper and Keyser, 2016). Fire resistant trees such as oaks have a thick bark protecting the cambium from damaging heat, but still they can be damaged by intense heat buildup. Trees and saplings with thinner bark have a greater chance of being damaged with fire scars, and possess higher risk of mortality. Fire can injure the lower boles of residual trees making them vulnerable to fungal diseases, pest attacks and woody decay (Dey and Schweitzer, 2015). Fire can also impose negative effects on soil organic matter and result in reduced soil fertility, especially when burning occurs under extremely low soil moisture conditions. Harper and Keyser (2016) explain that if fire is intense enough to consume the duff layer, there is a possibility of soil pores being clogged with fine particles of soil and carbon which would reduce soil infiltration and aeration. This would lead to surface runoff and soil erosion.

The negative effects of high-intensity, wildfires can be large. Most extreme stand replacing fires can be destructive and cause property damage and even loss of human lives (Arno and Fiedler, 2005). These wildfires release large quantities of sequestered carbon to the atmosphere, contributing to climate change (Stephens et al., 2009). The literature suggests that prescribed fire and natural fires (mostly low intensity) can be used to restore forestlands of North America that have undergone structural and compositional changes after decades of fire suppression. However, management decisions should be site-specific and should be adjusted depending on site history, current condition and future objectives.

Prescribed fire as a silvicultural practice to restore oak ecosystems

Prescribed burning can be used as a silvicultural tool in the management of upland oak ecosystems to restore the natural disturbance process historically experienced by these landscapes (Knapp et al., 2009). After decades of research on the topic, there are promising results in using prescribed burning to encourage oak regeneration, if used appropriately in combination with other silvicultural treatments such as mechanical thinning to reduce overstory stocking rates (Brose et al., 2013; Brose et al., 2014; Brose, 2014; Dey, 2014; Dey and Schweitzer, 2015; Knapp et al., 2009).

Restoration of oak ecosystems by using prescribed fire to encourage oak regeneration has become a widely-investigated research topic (Brose et al., 2006). Based on a review of fire-oak research, Brose et al. (2014), states that since the 1990s' fire-oak research has become much more prevalent and more diversified with respect to management objectives. Generally, all these studies consider the multiple facets of fire effects on oak ecosystems and try to determine what silvicultural solutions are best for oak regeneration. After many decades of researching this issue, a wide array of results encompasses evidence that fires enhanced, hindered, or had no effect in providing oak a competitive advantage in the regeneration pool. Brose et al. (2006) tried to dissect these different studies by means of stand structure, fire intensity and number of burns being used and their response. More recently, Brose et al. (2014) reviewed the current knowledge base to provide guidelines for utilizing prescribed burning for oak ecosystem restoration with additionally considering the season of burn.

If we consider the experimental designs used in all these studies being reviewed, we can see a wide spectrum of possible scenarios. It ranges from studies with a "single dormant-season fire with low intensity, in a mature stand" to "multiple growing-season fires with high intensity, in a cut stand". In addition, these oak stands vary in characteristics such as site quality (site index) and species composition. Therefore, it is easy to understand why every possible response of oak regeneration has be found under these highly varied experimental scenarios.

Regeneration response

Successful oak regeneration is a process that takes 5-20 years (Stringer, 2016). Its success depends on the presence of adequate advanced oak regeneration (around 4 feet tall) or stump sprouts. Having 100-200 or more seedlings per acre is vital to ensure adequate oak regeneration (Stringer, 2016). However, a common problem across the eastern oak forests is the absence of an oak regeneration pool in adequate abundance, especially in an environment with increasing competition from other tree species.

The two most important biological factors that govern oak regeneration response to prescribed fire are; 1) the development stage of the oak stand and, 2) the degree of root development of the oak reproduction (Brose et al., 2014). The presence of an already established oak reproduction (advanced oak regeneration), prior to a silvicultural treatment is vital for success (Stringer, 2016). Impact is influenced by two important biological characteristics of oak: hypogeal germination of oaks acorns, and root centric growth pattern. Due to hypogeal germination, oak cotyledons (where root collar and dormant buds are formed) remain in the acorn. Oak acorns are buried in soil by wildlife, are insulated by soil and protected from otherwise detrimental fires (Brose et al., 2006; Brose et al., 2014). After germination, oaks invest heavily in building a strong root system by preferentially storing carbohydrates in root systems (root-centric growth), as opposed to investing in heavy vegetative growth/ stem growth (shoot-centric growth) (Brose et al., 2006). This is where oaks usually loose the battle to competitors in a fire-free environment. Due to initial slow shoot growth, seedlings and saplings of competitor species with taller shoots quickly overtops oak seedlings. However, if a prescribed fire is introduced at this stage of stand development, all saplings would be top-killed. But, supported by a large root system, oaks can out-compete the competitor species by vigorously re-sprouting. To exploit this competitive advantage to the fullest, the light levels at the understory should be at an optimum level for oaks. With this foundational understanding, we can start to untangle the complex and contradictory mix of conclusions researchers have reported over the years. As stated earlier, the overall outcome of a treatment depends on how well it supported oak advance regeneration (if not already present), or released them from competition (if advanced regeneration is already present), by providing optimal understory light levels.

Site quality and fire intensity

Site quality is an important factor to be considered when decisions on treatments are made. Results indicate that in high-quality sites the understory light conditions are usually inadequate to support vigorous oak advanced regeneration. Oak seedlings in these stands usually lack their characteristic large root system due to low-light understory conditions. Therefore, low-intensity, single fires in these sites doesn't seem to enhance the competitive position of oak regeneration. In contrast, oak stands with sparser canopies (in lower-quality sites) has a better regeneration pool due to higher light levels, which can respond positively to a low-intensity surface burn. High-intensity burns will have an even more positive effect due to higher mid-story and overstory mortality of mesophytic species. However, as stated by Fox and Creighton (2016), high-intensity fires are not recommended in oak systems due to possible damage to residual, favored trees. The suggested alternative is to use mechanical thinning to reduce overstory stocking followed by a low-moderate intensity fire.

Fire frequency

The competitive position of oaks seems to increase as number of fires increase until it reaches a saturation point (Brose et al., 2014). With multiple burns, understory light levels would be enhanced while repeatedly killing competitive species and allowing oaks to re-sprout vigorously. However, with repeated dieback and re-sprouting, oak root stocks would diminish overtime. Therefore, it is important to have a fire-free period after a few burns allowing the re-sprouted oak seedlings to recruit into the sapling stage. If burn season is taken into consideration growing season fires are reported to be more effective in killing more stems and hardwood rootstock than dormant season fires, due to depleted root stocks at the beginning of the growing season (Brose et al., 2014; Knapp et al., 2009). For a program with multiple burns, the initial few burns could be during the growing season and then shift to dormant season burns, or alternate season of burn once the overstory stocking rates are reduced to a desirable level (Keyser et al., 2016).

Thinning

Another important factor being reported is the effect of cutting/ thinning prior to burning. In a mature forest stand, with low light levels, advanced oak regeneration cohort is lacking and oak root stocks are not well developed. Therefore, after a prescribed burn, competitor species may also thrive in the improved resource environment and can have negative effects on overall oak regeneration. Therefore, it may be necessary to introduce additional disturbance (mechanical thinning or harvesting) to establish some advance oak regeneration a few years before introducing a fire regime (Brose et al., 2006; Dey et al., 2016). This condition is more severe in high-quality sites as compared to low to medium quality xeric sites.

Studies of clear-cutting, shelterwood cutting and low-thinning with small gaps reveal that except for low-thinning, these silvicultural practices would enhance understory light conditions, encouraging new and existing oak seedling growth, rootstock development and release from competition (Brose et al., 2006; Dey et al., 2016). Effectiveness of cutting treatments also depends on the length of time between thinning and the burning, as waiting to burn until 2-3 years after thinning would provide sufficient light and time for vigorous root growth.

Fire-oak research studies implemented under varied combinations of site quality, burn season, fire intensity, thinning and number of burns, came to different conclusions on impact of fire on oak regeneration. As explained by Brose et al. (2014), these contradictory conclusions can be attributed to differences in study conditions. Fire was removed from these ecosystems for many decades, and any restoration efforts will take time, possibly years to decades of continuous management. It is unrealistic to expect complete structural change with a single burn.

Limitations of introducing a fire regime into a mature oak forest

To understand when, where and how to use fire for oak regeneration, it is necessary to understand the limitations and negative effects of introducing a fire regime into a mature oak forest. The main limitation would be the challenge of determining the best prescription, as management strategy should be site specific (Schweitzer et al., 2016). Decisions on the season of fire, intensity of fire, frequency of burning, the use of mechanical thinning/ harvest, and the interval between thinning and burning matters. Different combinations of factors will lead to different results, which also depend on site quality and history (Brose et al., 2006; Brose et al., 2014). Single, low intensity, dormant season fires with no thinning will have the least structural effect while multiple, growing season fires with high intensity and supplemented by some thinning or harvesting will have the greatest (Brose et al., 2014).

Another major limitation would be the prolonged length of time needed to reach the desired end status, which requires on-going commitment. Persistent management over 10 years or longer, with an alternative combination of monitoring, mechanical and chemical thinning, harvesting, and prescribed fires may be required to restore and maintain these oak systems (Dey et al., 2016; Keyser et al., 2016). This years-long commitment may discourage landowners, and if they give up half way through the process, oak regeneration can be unsuccessful.

Mature oak trees have fire resistant characteristics such as a thick bark and the ability to compartmentalize wounds quickly (Brose et al., 2014). But there might still be instances where mature trees are seriously damaged by fires. Damage is more likely when fuel accumulates around a tree either from thinning or downed timber, which increase fire intensity and prolongs heat exposure. Fire damage can significantly reduce timber value, which may be a concern for landowners. Due to this risk of damage, prescribed fire is not recommended on highly productive sites unless timber value is not a concern (Harper and Keyser, 2016). Fires intense enough to kill trees would also have the potential to injure lower boles of residual trees, making them vulnerable to fungal diseases, pest attacks and woody decay (Dey and Schweitzer, 2015).

As oaks are intermediate in tolerance of light, it is critical to generate a moderate level of light through overstory and mid-story removal. Compared to mechanical thinning, when using fire, there is less control over which trees will be killed and the spatial arrangement of dead trees when using fire (Dey et al., 2016). Therefore, this could lead to creation of more- or less-than desired light environments which would ultimately pose negative effects on oak regeneration.

Prescribed fires are detrimental for recently fallen acorns and small seedlings that do not have strong root systems to support re-sprouting (Brose et al., 2014). Widespread re-sprouting might amplify deer browsing issues. Another major concern with frequent burning is its effect on soil, where soil organic matter and carbon can be greatly reduced, leading to increased soil bulk density and reduce soil porosity and water holding capacity (Williams et al., 2012). If all these happen together, and without sufficient number of oak saplings and advanced regenerations, the overall effect of fire on oaks will be negative (Brose et al., 2014). With all these limitations and negative effects, extreme care should be taken in creating the best fire management prescription and introducing fire into mature oak forests.

Prescribed fire use in natural resource management

Prescribed fire is a vital land management practice used as a disturbance mechanism in restoring and managing North American landscapes (Arno and Fiedler, 2005; Brose et al., 2014; Johnson et al., 2009; Middendorf et al., 2009). The National Cohesive Wildland Fire Management Strategy (WFEC, 2014) in the United States recognizes fire as a natural process, and its use as a tool in creating resilient landscapes. Currently in the United States, prescribed fire is being used in rangeland, forestland and agricultural land management under a diverse array of environmental conditions.

The National Association of State Foresters (NASF) along with the Coalition of Prescribed Fire Councils (CPFC) have prepared the *"National Prescribed Fire Use Survey Report",* based on responses to a questionnaire from all 50 state forestry agencies in the country (Melvin, 2015). This survey is intended to understand; 1) the scale of prescribed fire use, 2) state-level supporting programs and 3) limiting factors affecting the use of prescribed fire. When interpreting results, it is important to understand that rangeland burning is reported as a forestry activity. The same geographic regions used for the National Cohesive Wildland Fire Management strategy were used in this report for consistency. The following discussion summarizes the main findings reported in the *2015 National Prescribed Fire Use Survey Report* (Melvin, 2015).

In 2014, approximately 11.7 million acres were treated with prescribed fire. Most (76%) of these fires occurred in forest and rangelands, while the remaining fires (24%) were agriculture related burnings. All three regions (northeast, southeast and west) had similar (to national) proportions between forest and agricultural burning. Compared to 2011, forest-related burning has increased slightly while agriculture related burnings have decreased by about 10 million acres. However, this difference reflects better reporting in 2014 from western states and errors associated with agricultural burn reporting. Compared at the regional scale, approximately 70% of forestry and agricultural prescribed fire activity is recorded from the southeast, while the northeast had the lowest (3%) fire activity. It is interesting to see this trend of higher prescribed fire activity in southeastern states compared to other regions of the country. Four states: Kansas, Oklahoma, Georgia and Florida, reported 1 million acres or more being burned in 2014. Apart from Kansas, the other three states belong to southeastern region. When fire suppression policies were adopted in 1930s throughout the United States, there was some allowance for continued prescribed fire use in southeast region (Williams, 2000). Importance of fire to maintain landscape resilience in this region had been recognized even in that era. This continued interest and recognition might be the underlying reason why prescribed fire use is higher in the southeast today. Kansas reported 1 million acres or more of forestry prescribed fire activity in 2014. However, the majority of these fires should be categorized as rangeland. This is an example where combining rangeland and forest burning into one group is misleading.

Only 24 states offered prescribed burn manager certification courses. However, this is a 41% increase compared to 2011. The number of prescribed fire councils increased by 24% (31 in

27 states). These results indicate a positive trend towards increased capacity and training of fire managers. As collaborations and partnerships are vital for successful land management, inter-agency cohesion, collaboration, partnerships, and mutual support is really important to achieve land management goals as a group. Eighty-two percent of states had some form of burn authorization or permitting. However, land managers, researcher and policy makers should be concerned about the status of agricultural burn tracking. Only 12 states (24%) tracked agricultural burns, whereas 33 states (66%) tracked forestry related burns (including rangeland burns).

The third and final objective of the survey was to identify limiting factors for the use of prescribed fire. Weather, capacity and air quality/ smoke management are the three most obstructive factors for prescribed fire use at the national level. These three factors combined together accounted for 72% of the lack of capacity. Understanding driving forces of weather, smoke management and optimal burn window were identified as key areas to be further studied for better use of prescribed fire. Towne and Kemp (2003) proposed alternatives to widen the current narrow burn window to deal with weather and smoke management issues.

This report successfully delivered important results and information of immense value for land managers, fire managers and researchers. However, it is important to repeat this survey every few years to understand the dynamic nature of prescribed fire use in United States.

Prescribed fire use in Kansas: Preserving the integrity of the Flint Hills

The Flint hills region in Kansas represents the largest contiguous tract of landscape remaining of the tallgrass prairie in North America (Middendorf et al., 2009; Ratajczak et al., 2016). North American grasslands, including the tallgrass prairie, were historically maintained with recurrent fires (Knapp et al., 2009). These fires were either naturally ignited from lightning strikes or were purposefully ignited by Native Americans (Knapp et al., 2009; Middendorf et al., 2009). This region is predominantly covered by warm-season grasses with a patchy abundance of forbes determined by fire and grazing activities (Knapp et al., 2009). Woodlands and oak savannahs can also be found scattered across the landscape mainly in riparian buffers, and in areas with higher precipitation and long fire return intervals (Knapp et al., 2009).

Woody encroachment, or the gradual conversion of C_4-dominated grasslands to savannahs and then to closed canopy forests, has been identified as a significant threat to the long-term persistence of the tallgrass prairie ecosystem (Bowles and Jones, 2013; Briggs et al., 2005; Engle et al., 2008; Kettle et al., 2000). Just 4% of the remaining portion of the tallgrass prairie in North America is still extent (Ratajczak et al., 2012). This change in vegetation communities is largely attributed to the alterations in historical fire regimes and land use pattern following European settlements in North America (Middendorf et al., 2009). Due to its geology, the Flint Hills region survived conversion to tillage agriculture and has become a prominent livestock grazing rangeland (Middendorf et al., 2009). Apart from grazing, the prairie ecosystem provides many services such as preservation of freshwater resources, soil erosion control, wildlife habitat and carbon sequestration (Briggs et al., 2005; Ratajczak et al., 2016). However, low burn frequency, increased livestock grazing pressure, nitrogen deposition, and projected increase in winter precipitation and atmospheric CO_2 levels could escalate woody encroachment probability in the Flint Hills (Briggs et al., 2005; Ratajczak et al., 2016). Therefore, the preservation of the Flint Hills in Kansas would largely depend on how successful the prescribed fire treatments would be in controlling long-term woody encroachment.

Based on long-term fire research and observational data Ratajczak et al. (2014) states that prescribed fire intervals greater than 3 years would favor a transition of grasslands to shrub lands overtime. Having fire return intervals greater than 10 years, or complete suppression would lead to a transition into woodlands over 30-50 years' time. Briggs et al. (2005) explains that once shrubs get established in these ecosystems, they would invade the surrounding grasslands overtime irrespective of fire frequency leading to a state where grasses and shrubs co-exist.

However, of particular concern is the establishment and expansion of Eastern redcedar *(Juniperus virginiana)*, a native evergreen tree species which has high growth rates (Briggs et al., 2002a; Ratajczak et al., 2016; Ratajczak et al., 2012). This would escalate the risk of uncontrollable woodland fires, reduce grazing potential of the grasslands and reduced biodiversity. Therefore, in order to maintain the tallgrass prairie intact, it is necessary to have a disturbance regime with fire return intervals of less than 3 years.

Ratajczak et al. (2016) reports that 56% of the grasslands in the Flint Hills region is burnt with a fire return interval greater than 3 years, making them vulnerable to conversion to shrub lands and then to woodlands over time. The remaining 43% of the grasslands are burnt approximately annually which would ensure their long-term preservation as grasslands. However, there are some concerns associated with annual burning such as homogenization of vegetation and avian communities, and more recently smoke dispersion and air quality issues (Ratajczak et al., 2016; Towne and Craine, 2016). Air quality and smoke management issues can be severe when smoke impacts highways and residential or urban areas, creating a social and human health issue. Therefore, land and fire managers can consider alternative approaches to managing these landscapes. There is a recent, increased interest in studying smoke management and air quality, which may provide better smoke management models for fire-managers in the future (Ratajczak et al., 2016).

One alternative is to burn outside the traditional spring burn window. Late spring burning (late April) has long being the norm in conducting prescribed burns in the Flint Hills of Kansas (Knapp et al., 2009). However, Towne and Craine, (2016) argue that expanding the burn window to start burning earlier in the dormant season is a possible alternative with potential to alleviate some air quality issues. At a minimum, this approach might alleviate smoke in areas close to highways and urban/ residential areas.

In managing these landscapes with fire, it is important to consider the significant role being played by livestock grazing. Species diversity in the grassland community was found to be maximized when they were infrequently (not annually, but less than a 3-year fire return interval) burnt and allowed moderate level of grazing by livestock (Collins and Calabrese, 2012).

Even though historical fire regimes have been altered, prescribed burning is used more often for natural resource management in this region compared to the eastern United States. This is mainly due to scientific management of the tallgrass prairie ecosystems and its embedded relationship with fire. Fire in woodlands is not as well accepted as grassland burning. However, due to the widespread use of fire in adjacent prairies, there is an opportunity to educate landowners in this region in its use in woodlands to promote oak regeneration.

Eastern redcedar encroachment in the forest-prairie ecotone of Kansas

As depicted in Figure 2-1, the transitional region between heavily forested Eastern United States and the grasslands of the Midwest is identified as the forest-prairie transitional region (Johnson et al., 2009).

This midcontinent forest-prairie transitional region/ ecotone of North America is currently exhibiting an extensive Eastern redcedar (*Juniperus virginiana)* (ERC) encroachment into the prairie ecosystem (Briggs et al., 2002a). It continues to expand in area and density particularly in Missouri, Nebraska, Kansas and Oklahoma, and drives major alterations in species composition and forest structure in this region, suppressing the previously dominant oak (*Quercus)* species (DeSantis et al., 2011; Meneguzzo and Liknes, 2015). Williams et al. (2013) found that eastern redcedar reduces litter quality and alters the soil microbial communities within oak woodlands. The symbiont association between arbuscular mycorrhizal (AM) fungi and eastern redcedar create a positive soil-microbial feedback encouraging rapid increase in eastern redcedar, and reducing the vigor of oak species (Williams et al., 2013).

In Kansas, the growing-stock volume of ERC increased by 15,000% between 1965 and 2010 (Moser et al., 2013). Since Kansas' 2.4 million acres of forest land constitutes only 5% of the State's total land base, the existing forested areas play an important role providing habitat for wildlife and providing many other ecological, economic and aesthetic benefits to the state. Oak/hickory is the predominant forest-type group in Kansas accounting for 55% of the total forest lands (Moser et al., 2013). Continued fire suppression in forestlands and adverse effects of climate change such as prolonged drought would continue the current trend of shifting *Quercus*-dominated forests to *Juniperus*-dominated forests in this region and adversely affect associated ecosystem services (DeSantis et al., 2011). Conversion of oak forests to ERC will intensify ERC expansion into the neighboring grasslands (Meneguzzo and Liknes, 2015).

Quantifying where ERC expansion is occurring most rapidly is essential for land managers to plan and manage control efforts (Meneguzzo and Liknes, 2015). Though ERC encroachment into the unique prairie ecosystem of the United States has been extensively documented (Briggs et al., 2002b; Briggs et al., 2002a; Ratajczak et al., 2016), the threat of ERC in driving a structural and species compositional change in forests is less commonly studied.

Remote sensing applications in natural forest management

Studying vegetation dynamics and spatio-temporal analysis

Remote sensing image analysis provides vital information for earth resource management applications. Remote sensing arguably provides the best platform to conduct large-area, multi-temporal scale studies and it is being widely used in monitoring vegetation dynamics and land cover change detection (Homer et al., 2012; Lillesand et al., 2014; Sankey et al., 2010; Vogelmann et al., 2009). Four categories of vegetation changes can be considered when using RS for monitoring landscape change: (1) abrupt change, (2) seasonal change, (3) gradual ecosystem change, and (4) short-term inconsequential change (Vogelmann et al., 2012).

NASA's Earth Observing System (EOS) is comprised of a series of polar-orbiting satellites used to observe and monitor key components of the global climate system. These observations are used to understand the earth as an integrated system and thereby understand human-induced and natural changes (Lillesand et al., 2014). This program was initiated in 1980-1990s and its first operational satellite system, Landsat-7, was launched on April 15, 1999. The main advantage of Landsat imagery is its long mission history. Although only Landsat 7 and 8 are included in the NASA EOS mission, the Landsat program started in 1972 and is still functioning. Therefore, it provides 45 years of continuous imagery with a 30-m spatial resolution for long-term vegetation dynamics studies (Lillesand et al., 2014; Vogelmann et al., 2012).

Remote sensing of vegetation in the optical portion of the electromagnetic spectrum (EMS) dominates vegetation studies over the use of microwave, thermal and other methodologies. Optical region includes the visible (4×10^{-7} to 7×10^{-7} m) and near to mid-infrared region (7×10^{-7} to 3×10^{-6} m) of the EMS (Jones and Vaughan, 2010).

Analysis of remote sensing imagery provides a powerful analytical tool for analyzing landscape dynamics. But, aerial image classification can be challenging. Advancements made in modern data acquisition techniques and sensor technology has generated vast quantities of remote sensing image data (Mennis and Guo, 2009). Therefore, a computational image classification process is required to convert these data into meaningful thematic information (Mountrakis et al., 2011). Due to their large size, high dimensionality, and complexity, efficient data mining algorithms and techniques are needed to accurately extract information from spatial data sets (Mennis and Guo, 2009).

The main objective of classification is to categorize each object or individual pixel into separate information classes. However, these class labels may be known or unknown at the beginning of analysis. If the investigator has prior knowledge of the geography of the area and is able to identify all the information classes present in that area, a supervised image classification approach can be followed. If the investigator prefers to first identify the natural groupings in the data, and use this information to assign labels to separable classes, an unsupervised classification approach should be followed (Mather and Tso, 2009). In supervised classification, interactive "training areas" for each class are used for statistical assessment of class reflectance, and this evaluation is extrapolated to the whole image (Thomson, 1998). In this approach, the analyst has more control over the process, but needs to be knowledgeable about the area.

Small Unmanned Aircraft Systems (sUAS) applications in forestry

The vast development of the use of small Unmanned Aerial Systems (sUAS) as a scientific discipline during recent years has provided opportunities for environmental scientists and natural resource managers (Colomina and Molina, 2014; Grenzdörffer et al., 2008; Lisein et al., 2013). small Unmanned Aircraft Systems have advantages of low operational costs, flexible control of spatial and temporal resolution and ability of high-intensity data collection, as compared to manned flights (Michez et al., 2016; Tang and Shao, 2015). However, current use of sUAS in forestry applications are still at an experimental stage (Tang and Shao, 2015).

There is a huge potential for incorporating sUAS as a management tool in the areas of tree plantation management, natural forest management and urban forestry. One of the main parameters required in managing these resources is tree canopy heights (Tuominen et al., 2015; Zarco-Tejada et al., 2014). Using high resolution aerial imagery and 3D point clouds captured from sUAS, it is possible to generate a digital surface model (DSM) with high accuracy (Lisein et al., 2013). A well-established method to measure canopy heights is to subtract a digital terrain model (DTM) which usually is obtained from a LiDAR dataset, from the DSM to obtain the canopy heights (Lim et al., 2015; Lisein et al., 2013).

The use of sUAS in forest fire monitoring and to help fire-fighting efforts has been recorded previously (Merino et al., 2012; Ollero and Merino, 2006). However, no studies were found where sUASs were effectively used in prescribed fire studies.

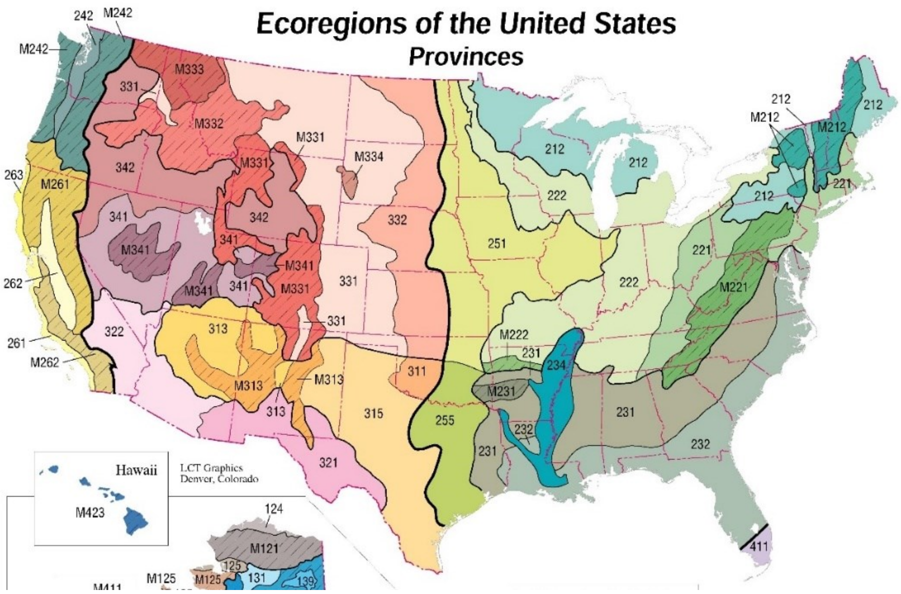

Figure 2-1. Ecoregions of the United States: The region corresponding to 251 and 255 together represents the forest-prairie transitional region (Bailey, 1994).

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Chapter 3 - Ecological Restoration of an Oak Woodland within the Forest-Prairie Ecotone of Kansas

Abstract

Conversion of mature oak (*Quercus spp*.) dominated woodlands to shade-tolerant species is a well-documented problem across the eastern United States. Oak woodland restoration within the forest-prairie ecotone of Kansas has not been systematically studied before. Hence, a 90-acre oak-dominated woodland is being used to study the effects of prescribed burning and mechanical thinning to encourage oak regeneration within this region. The experimental design is a 2 (burn) x 2 (thin) factorial in a repeated measures design. Burning and thinning treatments were administered in spring 2015 after conducting a pre-treatment stand inventory. Re-sampling was done after two-growing seasons in fall 2016. Pre-treatment inventory revealed oak dominance in the mature tree class, while undesired competitive species such as *Cercis canadensis*, *Ulmus americana* and *Juniperus virginiana* collectively dominated the seedling and sapling classes. Thinning caused canopy cover to reduce significantly, and seedling of both oaks and competitor species thrived under enhanced understory light environments. The burn treatment on the other hand controlled understory shrubs and competitive woody vegetation, while encouraging oak regeneration. Hence, the most promising results were observed when thinning and burning were combined. Additional management is recommended to further suppress competition and support restoration.

Introduction

Historical fire regimes characterized by recurrent, landscape-level fires were pivotal for the development and sustenance of the eastern oak forests of the United States (Abrams, 2016). Oaks (*Quercus spp.*) benefited from such periodic fires securing a competitive position in the regeneration pool (Brose et al., 2014). With decades of fire suppression, these mature forests have developed into a closed canopy status with thick mid-stories. This has resulted in cooling, dampening and shading (mesophication) of the understories with leaf litter layers being less conducive to fire (Abrams, 2016; Nowacki and Abrams, 2008). Being intermediate in shade-tolerance, oak seedlings are often outcompeted by shade-tolerant, fire-sensitive, mesophytic species under these conditions (Schweitzer et al., 2016). This oak regeneration issue in eastern forests is well documented, and many silvicultural prescriptions for restoration are being investigated through long-term systematic research (Brose et al., 2014; Brose, 2014; Dey, 2014; Dey et al., 2016). However, peer-reviewed literature on the oak regeneration issue within North America's mid-continental forest-prairie ecotone is lacking. Similarly, the use of prescribed fire as a silvicultural tool for restoration of oak ecosystems within the forest-prairie ecotone of Kansas has not being systematically studied.

Upland oak sites in Kansas belong to the "oak savannah and prairie region", one of the four primary oak growing regions in the eastern United States (Oswalt and Olson, 2016). This transitional region lies between the heavily forested eastern United States and the great grasslands to the west. Hence, the natural vegetation in this forest-prairie ecotone is a mix of both forests and grasslands (Johnson et al., 2009; Oswalt and Olson, 2016). Changing fire regimes with the advent of fire suppression policies altered the species composition and vegetation structure in the mid-continent forest-prairie ecotone of the United States (Briggs et al., 2002b; DeSantis et al., 2011). Woodlands in this region are one of the greatly imperiled ecosystems in North America, where agriculture has replaced fire as the restrictive agent, marginalizing woodlands/forests to riparian zones and areas with high slopes that are not suitable for agriculture (Johnson et al., 2009; Oswalt and Olson, 2016). Studies conducted in the late 1980s and early 1990s found that mainly two oak species, bur oak (*Quercus macrocarpa*) in mesic sties and chinquapin oak (*Quercus muhlenbergii*) in steeper xeric sites dominates the woodlands of northeast Kansas (Abrams, 1986). Furthermore, it was predicted that continued fire suppression in these landscapes would bring major change to the composition of these woodlands in the future. Hackberry (*Celtis occidentalis*) was observed to be gradually replacing bur oak in mesic sites, and eastern redbud (*Cercis canadensis*) is threatening chinquapin oak in xeric sites (Abrams, 1992). It is evident through Forest Inventory and Analysis (FIA) data that density of oak forests in Kansas has increased since 1990s. If conditions prevail with no natural and/or human-caused disturbances, shade-intolerant species will be favored suppressing oak regeneration and recruitment (Moser et al., 2013). Recent research in the eastern hardwood forests has shown that prescribed fire can provide positive results in promoting oak regeneration (Brose et al., 2014), yet this has not been widely considered as a management practice in Kansas. Nonetheless, opportunities for this approach do exist and should be especially well-suited for use in the Flint Hills region because of the acceptance of prescribed fire for native grass management and the historical occurrence of fire (Knapp et al., 2009).

In many ecosystems in the eastern United States, oaks do not form the climax forest, and are considered a mid-successional species (Burhans et al., 2016). Historically, fire acted as a periodic disturbance to the successional trajectory in these ecosystems and maintained a community with fire-dependent xerophytic species such as oaks (Nowacki and Abrams, 2008).

Many ecologists argue that this control of disturbance through fire suppression and allowing succession to take its course would result in “unnatural forests” and therefore requires science-based management to mimic the natural disturbance process (Burhans et al., 2016). The re-introduction of fire and other disturbances would help promote oak regeneration and restore oak ecosystems.

After many decades of research on oak regeneration in eastern forests, the scientific community is presented with a wide array of results, where there is evidence that fires enhanced, hindered or had no effect (Brose et al., 2014). However, available literature covers a wide spectrum of possible scenarios including number of fire treatments, season of fire, fire intensity, initial site quality and species composition, and incorporation of another silvicultural practice such as thinning. Therefore, it is possible to observe every oak regeneration response under highly varied experimental scenarios. Overall, there are promising results in using prescribed burning to encourage oak regeneration, if used appropriately in combination with other silvicultural treatments such as mechanical thinning (Brose et al., 2014; Dey et al., 2016; Knapp et al., 2009). The current body of knowledge is largely based on research conducted in eastern forest ecosystems where the conditions are vastly different from oak woodlands in the forest-prairie ecotone. Therefore, application of management prescriptions based on available literature should be done conservatively. Long-term, field-based research conducted within this region would provide vital information for land managers to better manage oak woodlands with similar conditions. This research project was instigated as the stepping stone in fulfilling this need, and this manuscript discusses the results after the first three years of what will be a long-term research venture. The main objective of this study is to assess the effectiveness of using prescribed fire and mechanical thinning to encourage oak regeneration in the forest-prairie ecotone of Kansas.

Methods

Study site and experimental design

The project site is located north of Manhattan, Kansas, on the western edge of Tuttle Creek Reservoir (GPS location: 96 40'41.316"W 39 19'37.983"N). The 145 acre tract, part of the Howe Natural Resources Education Center, is owned by the Department of Horticulture and Natural Resources, Kansas State University. It is composed of a mix of upland oak and eastern redcedar (*Juniperus virginiana)* forest types (Figure 3-1), with native grass hay meadows, typical of many properties in the region. However, current research is limited to the portion of the property that is composed of the oak forest type.

The site index was assessed by extracting increment-core samples from 15 chinquapin oak trees, selected from different locations of the entire study area. Chinquapin oak was used as it is the most abundant species. Free growing, dominant or codominant trees with no signs of injuries or diseases were selected. The average age of the trees were 72 years with an average height of 49 ft. Site index curves for chestnut oak (*Quercus prinus)* in the central states (Appendix C) was used in the assessment (Carmean, 1971). It was estimated that this woodland has a site index of 40, which can be inferred as a low quality site.

The study area was delineated into 12 management units (compartments), ranging in size from 6-10 acres. Compartment boundaries followed the natural drainages to facilitate treatment boundary establishment, and act as cost-effective fire-breaks. Based on the topography, study area was divided into three blocks where each block contains four compartments. The treatment structure is a two-way factorial with two levels of burn (burn and no-burn) and two levels of thin

(thin and no-thin). An individual block was split into two 2-compartment units to randomly assign the burn treatment. Each of these 2-compartment units were split again into 1-compartment units to randomly assign the thinning treatment. Thus, experimental unit for burn treatment is the large 2-compartment unit (whole-plot), while an individual compartment (split-plot) serves as the experimental unit for thinning. In total, 92 permanent data collection plots (circular plots) were established throughout the site with a frequency of at least 1 plot per acre (Figure 3-2). Since there are more than one data collection plot within each experimental unit, they are treated as sub-sampling by design. These same plots will be used to collect stand inventory data repeatedly, over the years. At this stage of the project, there are two time points where 2016 inventory data (two growing seasons post-treatment) will be compared with 2014 (pre-treatment) inventory to assess initial treatment effects. This assignment of treatments in the field constructs an experimental design of randomized complete block design in a split-plot with sub-sampling and repeated measures. The experimental design allows four treatment combinations within a block; "burn only" (B), "thin only" (T), "burn and thin combined" (BT) and a no treatment "control" (C) for investigation.

Treatments

The pre-treatment inventory in 2014 revealed that all the compartments are over-stocked with a stocking percentage over 60% (8 compartments over 80%). For optimum oak regeneration response through enhanced light conditions at ground floor, the long-term overstory thinning target is to reduce the stocking to be less than 60% (B-line in the Gingrich stocking diagram in Appendix D) (Gingrich, 1967). However, if the number of competitive advanced oak seedlings present in the stand is insufficient at the time of overstory harvest, regeneration failures could occur due to competition from other hardwood species (Dey, 2014; Miller et al., 2017).

Therefore, with the initial condition of the woodland, it was decided to reach the target gradually with multiple preparatory treatments of thinning and burning. The initial thinning treatment was conducted in January 2015 with the following prescription; *trees:* remove 25 trees per acre mainly Eastern redcedar (ERC), American elm (*Ulmus americana*), hackberry and Eastern redbud, and *saplings:* remove 50 stems per acre of American elm, Eastern redbud, Eastern redcedar and hackberry. Saplings were completely cut and treated with a chemical mix of 25% Garlon-4 mixed with diesel fuel at 75% to suppress re-sprouting, and the trees were single girdled.

The burn treatment was conducted on the 21st of April 2015 by the Kansas Forest Service. A fire that would occur between leaf abscission in autumn and leaf expansion in the following spring is known as a dormant season fire (Brose et al., 2014). This late spring burn therefore can be considered as a dormant season fire as the leaves of the mesophytic hardwood seedlings (eastern redbud, hackberry and American elm) were less than 50 percent expanded. Since no hardwood photosynthesis has started, the root stock nutrient levels of the seedlings are at their minimum by the end of the dormant season. Due to its root centric growth, oaks will have a stronger root system with nutrients compared to its competitor species. This provides them a competitive advantage to re-sprout vigorously following a surface burn. Air temperature at ignition was 75 ºF, with a relative humidity of 33% and a 20 ft. wind speed of 4-6 mph. Fire behavior was mild in most places with 6-12 in. flame length and 5-10 ft./ min spread. Pockets of cut 10-hr and 100-hr fuel in the thinned compartments caused flare-ups of 5-20 ft. flame height, with no impact on rate of spread.

Data collection

Data collection was conducted at the 92 circular plots. At each plot, all trees larger than 5 inches in diameter at breast height (dbh) were measured on a 1/10 acre fixed-radius area (37.2 ft. radius). Two microplots were established at each plot location, located at 18.5 ft. from plot center on bearings of 90 degrees (east) and 270 degrees (west) from plot center (Figure 3-3). In these microplots, a 1/100 acre (11.8 ft. radius) area was measured to collect sapling data for trees 1.0-4.9 in. dbh. This information includes species, dbh, and specific notes about the sub-plot. At the center of each microplot, a tally was conducted on a 1/300 acre area (6.8 ft. radius) to include the number of live tree seedlings present by species. As per Forest Inventory and Analysis (FIA) protocol, criteria for seedlings were that hardwood seedlings must be at least 12 inches in height and conifer seedlings must be at least 6 inches in height.

Prior to the burn treatment in spring 2015, fuel loading was measured and repeated immediately after the burn to evaluate fuel consumption and assess fire behavior and fire effects. All the trees and saplings within 30 ft. from the plot center were assessed for burn scars and the scorch heights recorded following the burn as a measure of fire intensity. However due to their complexity, burn scar evealuations, fuel loading assessment data and interpretations of fire behavior and fire effects are not presented here.

Seedlings of oaks and its main competitor in the regeneration pool, eastern redbud were tagged (approximately 20-25 per species within each compartment) to assess immediate effects of the burn treatment on seedlings. Seedling height and basal diameter (diameter at 1 in. above the root collar) were measured. Canopy and understory vegetation-cover were assessed employing point-intercept transect sampling method (Hoover, 2008). Number of shrub/herb intercepts and their heights were recorded along two 50-ft. transects. Transects were placed at 90 degrees (east) and 270 degrees (west) from plot center, with a sampling interval of 5ft. The same transects and sampling interval were used to estimate canopy-cover percentage for each plot using a GRS densiometer (Geographic Resource Solutions, Arcata, California, USA).

Data processing and statistical analyses

During the data processing step, count datasets for trees, saplings and seedlings were converted to trees per acre (TPA), saplings per acre (SapPA) and seedlings per acre (SedPA) values by species. The dbh data for trees and saplings were used to calculate basal area per acre (BA) by species. Due to sparseness in the data for certain species, the final analysis was focused on the total values and then the most abundant species at each size class. Responses for chinquapin oak, bur oak (*Quercus macrocarpa)* and black oak (*Quercus velutina)* were combined to get a total response for oaks to be used in the analyses.

Data analysis was conducted using the GLIMMIX procedure of SAS (version 9.4, SAS Inst. Inc.). Vegetation structure and composition was analyzed for trees (> 5.0 in. dbh), saplings (1-4.9 in. dbh) and seedlings (< 1.0 in. dbh) separately. Three analyses were conducted for TPA dataset in which the response variables were the total, oaks and ERC. Four analyses were conducted for SapPA dataset with the response variables of total, oaks, ERC and American elm. Similarly, the response variables of total, oaks, eastern redbud and ERC were used for the SedPA dataset. The same combination of response variables for trees and saplings were used to analyze the tree and sapling BA datasets. Burn, thin and time factors were treated as fixed effects with block being the random effect. For oak, redbud, and total SedPA analyses the lognormal distribution with identity link function provided the best description of the residuals. For the rest, a normal distribution with an identity link function was utilized.

For tagged seedlings of oaks and eastern redbuds, the propotion of "top-killed", "top-killed and re-sprouting", and "not-affected" were analysed separately. The effect of initial seedling height and basal diameter on response to fire was assessed. Treatment factor levels under investigation for this analysis were B and BT. These analyses along with canopy, and shrub cover proportions used a binomial distribution with a logit link function. Overdisperion was checked by employing integral approximation to likelihood with laplace method, and Newton-Raphson with ridging was specified as non-linear optimization method. These optimizations ensured a more stable model in analysing the discrete proportion responses. Understory height analysis was performed using a normal distribution.

In all the analyses, the residual plots were investigated to check model assumptions. Appropriate descriptions of the variances were utilized for models with heterogeneous residual variances. The Kenward Rogers denominator degrees of freedom method and Tukey-Kramer adjustment for multiple comparisons were used. LSMEANS (least squares means) and PDIFF (pairwise differences) options of SAS were used for multiple comparisons. Type III test of fixed effects was employed and means were considered statistically significantly different at a *P*-value of < 0.05.

Results

Vegetation structure and composition

Pre-treatment woodland inventory in Fall 2014 revealed that the mature tree class is dominated by oaks with a percentage composition of 54% (Table 3-1). However, the same level of dominance is not present at sapling (17% oaks) or seedling stages (18% oaks). Collectively, 63% of the seedlings were composed of undesired competitior species such as eastern redbud, hackberry, American elm and ERC. Eastern redcedar, which is a tree species with rapid encroachment into prairie grasslands (Briggs et al., 2002a), composed 11% of the mature tree class. It also was the second most abundant species at the sapling stage with 18.5% in composition. All the compartments were at fully stocked level, with an average basal area of 100 ft^2/acre and 162 TPA.

As revealed by pre and post-treatment comparisons, there was not enough evidence for a significant three-way interaction between burn, thin and time fixed effects for total TPA. However, the two-way interaction between thin and time was significant ($P < 0.01$). On average, the total TPA reduced by 20 with the thinning treatment, averaged across the two burn treatment levels (burn and no-burn). The statistically significant reduction in total TPA in T and BT treatments (Table 3-2) therefore are driven by the thinning effect. Similarly, thin by time interaction effect was statistically significant for total BA even though it is not reflected with lsmeans comparison for treatment combinations in Table 3-2. Pairwise comparison of lsmeans for treatment combinations are statistically meaningful only when there is a significant three-way interaction between the fixed effects. The total BA reduced by 4.6 ft^2/acre between the two inventories, with the thinning treatment, after averaging across burning. None of the effects were found to be significant for oak TPA and BA estimates. In contrast, the three-way interaction was found to be significant for ERC TPA ($P = 0.04$). The selective thinning of ERC within the thinning prescription has signifcantly reduced its TPA estimates for the T treatment. The number of ERC trees decreased within BT treatment was not statistically significant, and could be due to the low initial number of ERC trees. The same response was observed for ERC BA, which can be explained by the significant two-way interaction between thin and time ($P < 0.01$).

Similar to total TPA, the significant thin by time interaction effect ($P < 0.05$) infer that total SapPA difference between years depends on the level of thinning, averaged across the burn treatments. Once the thin by time pairwise differences were examined, statistically significant reductions in total SapPA estimates were observed with both "no thin" (42 SapPA, $P = 0.03$) and "thin" (82 SapPA, $P < 0.01$) treatment levels, after averaging across two burn treatment levels. This suggests that some mortality that can be attributed to burning, but when it is combined with thinning the effect is much stronger. Oak SapPA was not significantly affected with any of the treatment combinations (Table 3-3). For American elm SapPA, the three-way interaction effect was significant ($P < 0.01$). A significant reduction in American elm TPA is observed only with the combined effects of burn and thin treatments. The thin by time two-way interaction was again found to be significant for ERC SapPA ($P = 0.03$). After averaging across burning, thining effect imposed a significant reduction of ERC Saplings by 23 SapPA in 2016, compared to pre-treatment condition. However, though there is a clear negative trend in ERC SapPA with T and BT treatments, pairwise differences did not yield a statistical significance. Considering sapling BA, a significant three-way interaction for total sapling BA ($P = 0.03$) was evident. This is revealed by a significant reduction in total sapling BA with the BT treatment, similar to the observation with total SapPA. However, no statistically significant changes in sapling BA was observed for oaks, American elm and ERC (Table 3-3).

The three-way burn, thin and time interaction effect was statistically significant for total ($P < 0.01$), oaks ($P = 0.02$) and eastern redbud ($P = 0.01$) SedPA. For ERC, there was not enough evidence for a significant three-way interaction effect. However, the two-way burn by time interaction effect was significant ($P < 0.01$). Total SedPA increased by 1750 with the T treatment (Table 3-4). In contrast, there was not enough evidence in support of a significance for the observed changes in SedPA under other three treatment combinations (Figure 3-6). Only B treatment effectively increased the oak seedling abundance with a significant effect ($P < 0.01$). Eastern redbud SedPA showed significant increases with T (203% increase, $P < 0.01$) and C (74%, $P = 0.04$) treatments. The B (52%) treatment had a restricted increase, while BT (1%) treatment combination demonstrating the most promising control over redbud expansion. In contrast to the effects with redbud, the B and BT treatment combinations showed significant impacts on ERC SedPA. More precisely, it is the significant burn by time interaction that prompted this significant change. On average, 113 ERC SedPA were killed by the burn treatment, averaged across the two levels of thinning (thin and no-thin).

Seedling response to burn

There was not enough evidence of a significant difference between initial seedling basal diameters of the tagged seedlings under investigation with B and BT treatments. On average, eastern redbuds (29 in.) were significantly taller than oak seedlings (18 in.) in the BT treatment ($P < 0.01$). Conversely, they didn't differ significantly in B treatment. There was not enough evidence of a significant two-way treatment by species interaction for "top-killed" burn response. However, both species ($P = 0.04$) and treatment ($P = 0.04$) factor effects were significant. The BT treatment caused a significantly higher seedling top-killing (45 %), compared to B treatment (20 %), averaged across the two species. Eastern redbud had a significantly higher seedling top-killing (44 %), compared to oaks (21 %), averaged across the two treatments. None of the effects were evident to be significant for "top-killed and re-sprouting" and "not affected" proportions (Figure 3-7). There was not enough evidence in support of initial diameter effect on fire response for seedlings. In contrast, the two-way treatment by response interaction effect was significant ($P = 0.02$) for initial seedling heights. On average, seedlings that were "not-affected" within the B treatment was evident to be significantly taller than the seedlings that were “top-killed” or “top-killed and re-sprouting”. Within the BT treatment, initial seedling heights didn’t seem to be a decisive factor in burn response.

Canopy and understory vegetation cover

The three-way burn, thin by time interaction effect was not evident to be significant for canopy cover percentage (Table 3-5). Thin by time interaction effect, however, was statistically significant ($P = 0.02$). The thinning treatment, averaged acrossed the burn treatment levels has triggered a significant reduction in canopy cover ($P = 0.03$). In contrast, it was the burn by time interaction effect that was evident to be significant for understory shrub cover ($P < 0.01$) and understory vegetation height ($P = 0.02$). Averaged across the two thinning levels, the burn treatment caused an 11-inch reduction in average understory vegetation height ($P < 0.01$).

Discussion

In summary, these results suggests that any kind of management intervention can influence species composition changes within the woodland. The control treatment provides valuable insights for comparisons. With no management, eastern redbud would continue to expand within the regeneration pool. Coupled with persisting over-stocked conditions and reduced light environments, the oak regeneration would be further suppressed. The thinning treatment effectively imposed desired changes to both tree and sapling classes. The decrease of total TPA by 20 and total SapPA by 82, both which are attributable to the thinning effect, confirms that the thinning treatment has achieved its initial treatment prescription targets (25 trees and 50 sapling stems, of competitive species). ERC, which is a major competitive species was effectively controlled by thinning at both tree and sapling classes. Thinning contributed to control Americam elm saplings as well. However, the increased sunlight reaching the understory through the mid-story and overstory thinning favored both oaks and its competitive species, when thinning was not combined with burning. The T treatment is the only treatment that caused the total SedPA to increase significantly. Due to its competitiveness, eastern redbud and ERC would easily outcompete oaks in this enhanced light environment if conditions persist. In contrast, the burning treatment controlled the competive species while encouraging oak regeneration. The most promising results were observed when thinning and burning was combined. The thinning process controlled the competitive species in the mid and over-story, whereas the burning treatment provided a competitive advantage for oaks in re-sprouting after top kill. The extra fuel added by the thinning treatment resulted in the BT treatment to have a higher fire intensity and fire effects (Galgamuwa et al., 2017). The BT treatment combination would result in positive effects on oak regenereation success, in the long-term through effective control of competitive species, reduced understory vegetation competition and higher consumption of fuel and downed woody debris.

Eastern redbud, the major competitive species at the seedling stage, re-sprouted successfully after the burn similarly to oaks. Physiologically, oaks demonstrate a root-centric growth pattern where their re-sprouting is supported by a strong root system with nutrition reserves. Therefore, they have a strong propensity to re-sprout even after multiple fires. In contrast, competitive species such as eastern redbud show a shoot centric growth where they invest in shoot growth with comparatively less root reserves. Therefore, their re-sprouting ability is diminished with multiple fires. While repeated fires would help oaks to outcompete other species, optimum light environments for oak regeneration need to be made by gradual mid and over-story thinning. Hence, continued management of the stand with repeated burning and thinning is necessay to successfully restore this oak woodland.

Compared to studies conducted on eastern deciduous forests with medium to high quality sites, this woodland had lower site quality (site index 40). Higher-quality sites often have poor understory light conditions that do not favor vigorous oak advanced regeneration, with large root systems. Therefore, single low-intensity fires don’t seem to enhance the competitive position of oak regeneration (Fox and Creighton, 2016) which appears to require multiple thinning treatments with longer time intervals between thinning and burning to allow establishment of advanced oak regeneration. Conversely, stands in lower-quality sites have a better oak regeneration pool in response to better light levels, and can respond positively to a low-intensity surface burn. It is suspected as one reason why this particular site responded positively to a single thinning and burning treatment with a four-month time interval. However, as stated before, repeated fires should further suppress eastern redbud, the main competitive species within the regeneration pool, improving oaks competitive position. These results confirm the importance of continuing this study with multiple thinning and burning treatments, with varied time intervals to investigate optimum silvicultural prescriptions suited for this region.

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Figure 3-1. Study Area delineated into 12 compartments. Eastern redcedar areas are represented in darker color

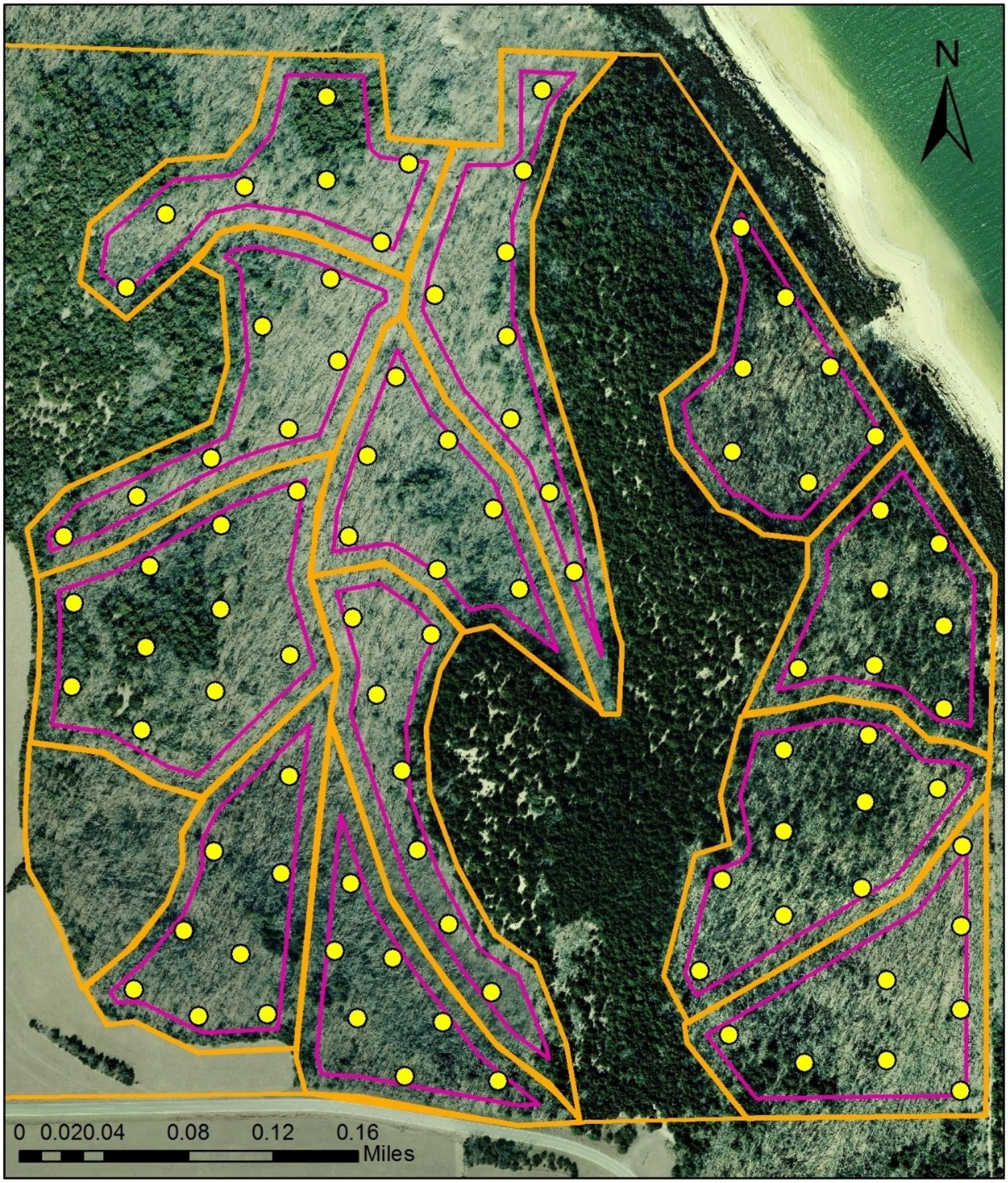


Figure 3-2. Permanent Data Collection Points

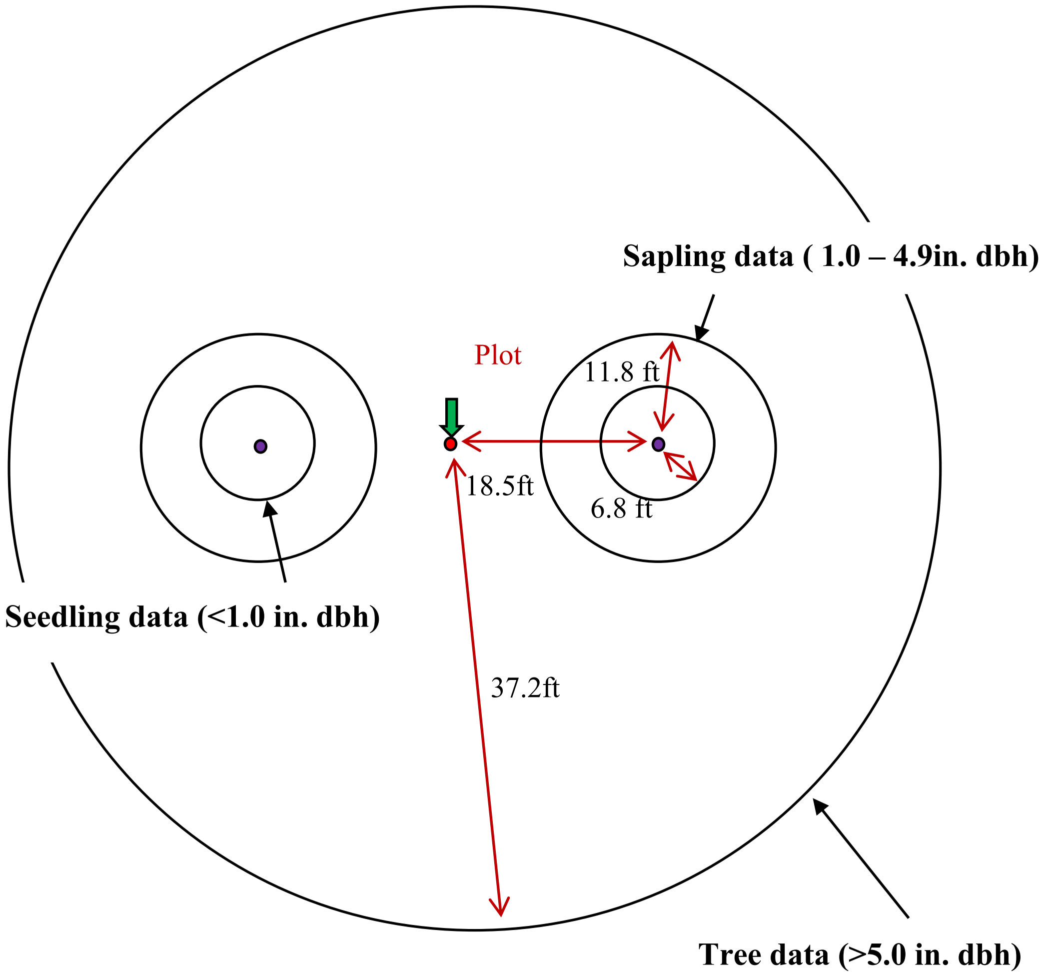


Figure 3-3. Permanent data collection plot structure

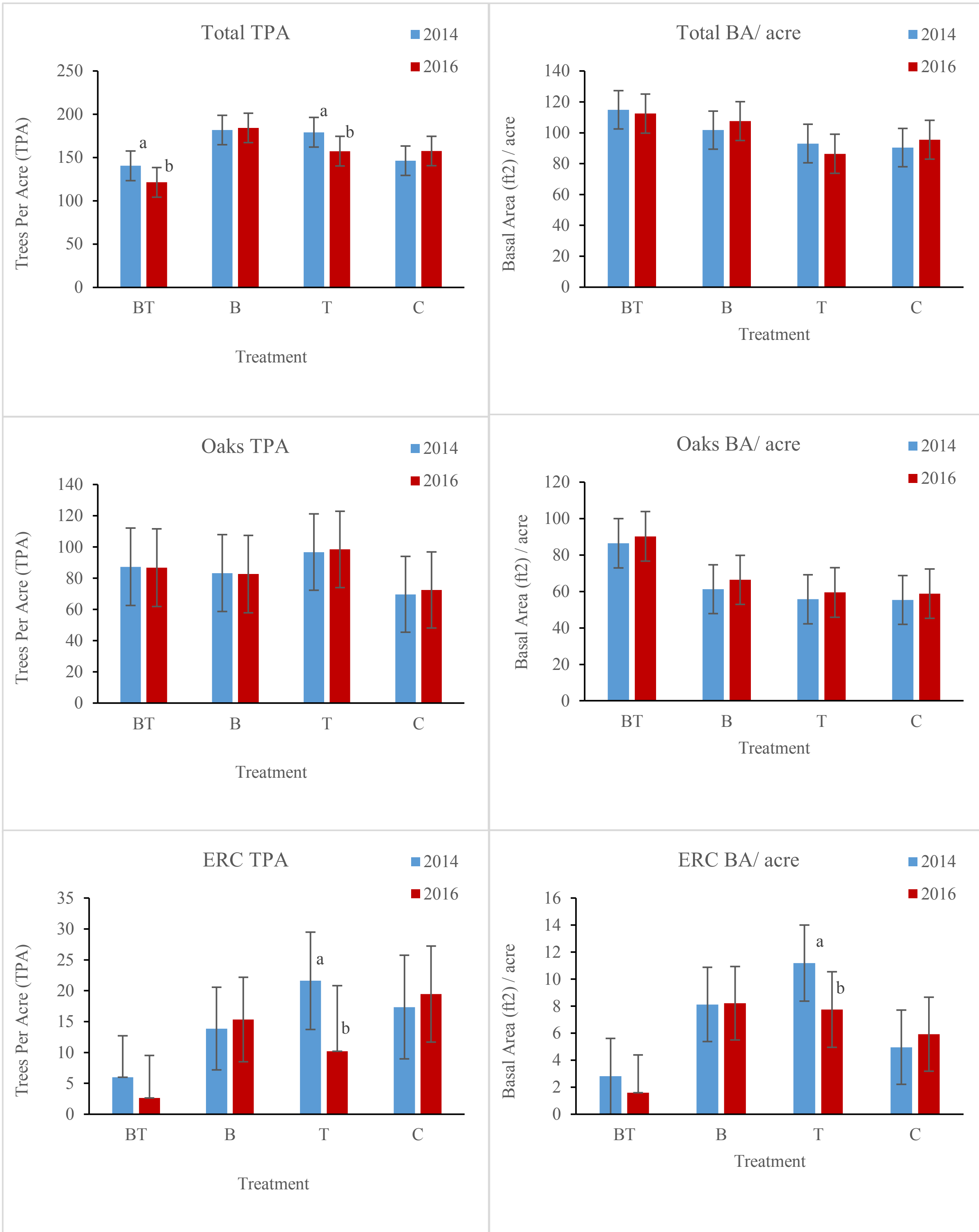


Figure 3-4. Trees per acre (left) and Basal Area Per acre (right) for the a) Total, b) Oaks c) Eastern redcedar

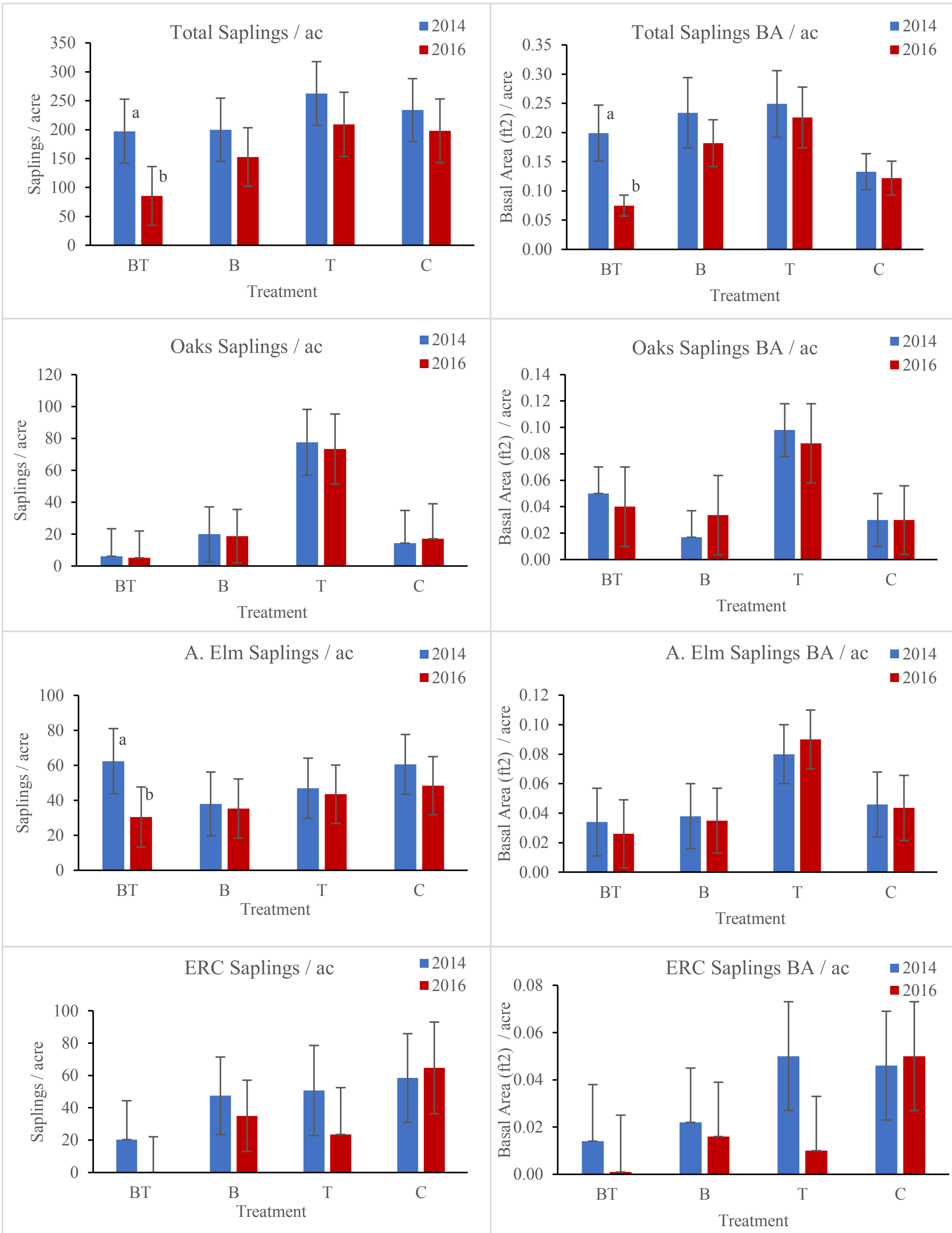


Figure 3-5. Saplings per acre (left) and Sapling Basal Area Per acre (right) for a) Total, b) Oaks c) American Elm d) Eastern redcedar

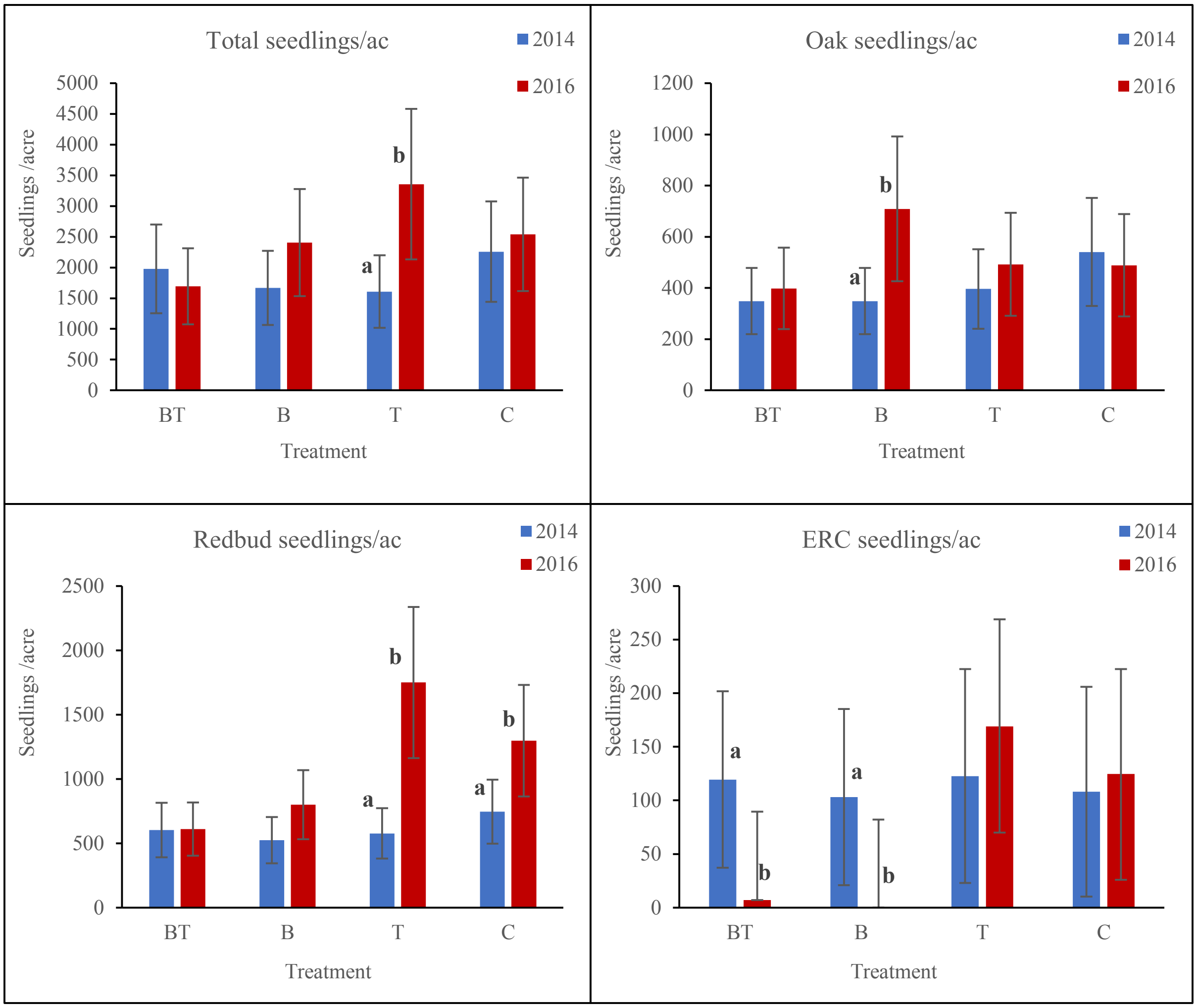
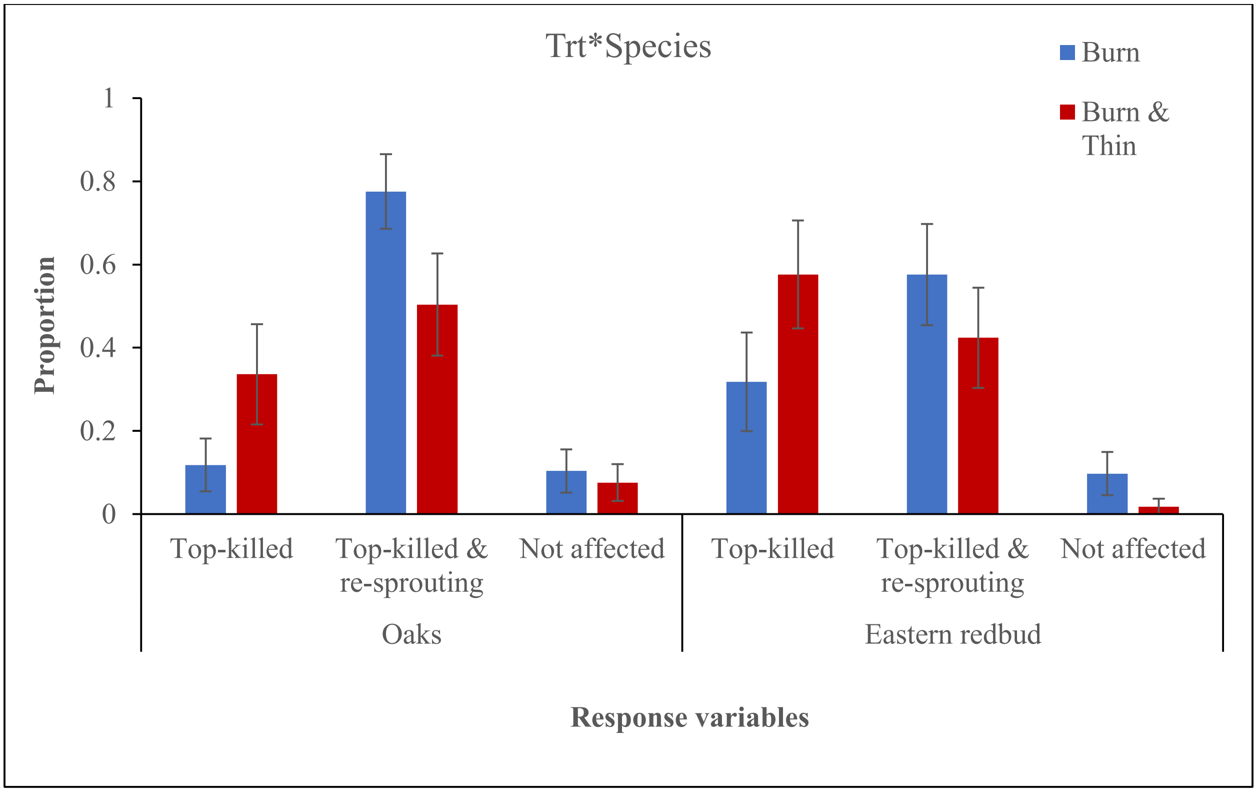


Figure 3-6. Seedlings per acre for a) Total, b) Oaks c) Eastern redbud d) Eastern redcedar



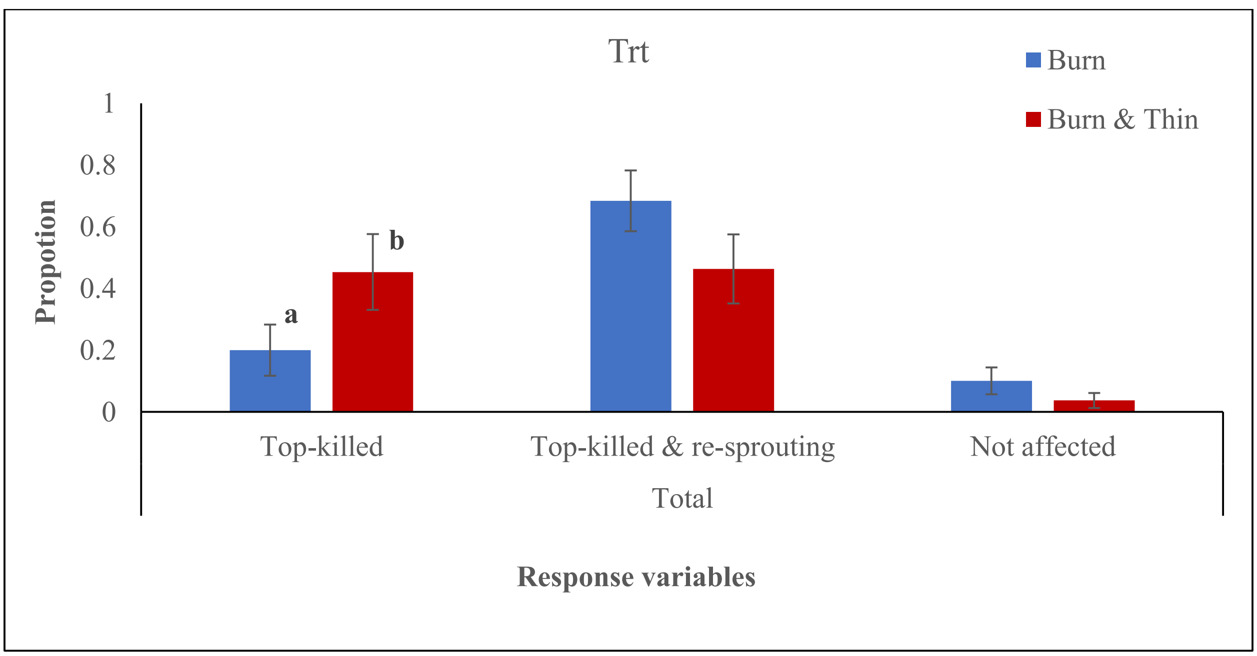


Figure 3-7. Tagged seedling responses

Table 3-1. Species composition of the entire study area at pre-treatment inventory

Common Name	Scientific Name	Percentage (%) composition
---------------------------- **Trees (Composition by Trees Per Acre)** -------------------------------		
Chinquapin oak	*Quercus muehlenbergii*	46.5
Eastern redcedar	*Juniperus virginiana*	11.2
Bitternut hickory	*Carya cordiformis*	9.3
American elm	*Ulmus americana*	7.7
Bur oak	*Quercus macrocarpa*	7.0
Black walnut	*Juglans nigra*	6.6
Hackberry	*Celtis occidentalis*	4.5
Red mulberry	*Morus rubra*	2.4
Eastern redbud	*Cercis canadensis*	1.7
Green ash	*Fraxinus pennsylvanica*	1.0
Kentucky coffee tree	*Gymnocladus dioica*	0.7
Black oak	*Quercus velutina*	0.5
Honeylocust	*Gleditsia triacanthos*	0.5
Osage-Orange	*Maclura pomifera*	0.3
--------------------------- **Saplings (Composition by Saplings Per Acre)** --------------------------		
American elm	*Ulmus americana*	23.0
Eastern redcedar	*Juniperus virginiana*	18.5
Chinquapin oak	*Quercus muehlenbergii*	16.6
Bitternut hickory	*Carya cordiformis*	14.8
Eastern redbud	*Cercis canadensis*	13.9
Hackberry	*Celtis occidentalis*	7.1
Red mulberry	*Morus rubra*	3.5
Black walnut	*Juglans nigra*	1.5
Bur oak	*Quercus macrocarpa*	0.4
Osage Orange	*Maclura pomifera*	0.4
Black oak	*Quercus velutina*	0.2
-------------------------- **Seedlings (Composition by Seedlings Per Acre)** ------------------------		
Eastern redbud	*Cercis canadensis*	30.7
Hackberry	*Celtis occidentalis*	20.1
Chinquapin oak	*Quercus muehlenbergii*	16.7
Bitternut hickory	*Carya cordiformis*	15.1
American elm	*Ulmus americana*	6.3
Eastern redcedar	*Juniperus virginiana*	5.8
Honeylocust	*Gleditsia triacanthos*	1.7
Red mulberry	*Morus rubra*	1.6
Bur oak	*Quercus macrocarpa*	0.9
Black walnut	*Juglans nigra*	0.7
Black oak	*Quercus velutina*	0.4

Table 3-2. Pre-and Post-comparison of TPA and BA/acre

Response Variable	Control (n = 24)		Thin (n = 22)		Burn (n = 24)		Burn & Thin (n = 22)	
	2014	**2016**	**2014**	**2016**	**2014**	**2016**	**2014**	**2016**
	---------- **Trees per acre** ----------							
Total	146	157	**179 a**	**157 b**	182	184	**141 a**	**121 b**
Oaks	70	73	97	99	83	83	87	87
ERC	17	19	**22 a**	**10 b**	14	15	6	3
	---------- **Tree Basal area (ft^2/ac)** ----------							
Total	90	96	93	86	102	108	115	112
Oaks	55	59	56	60	61	66	87	90
ERC	5	6	**11 a**	**8 b**	8	8	3	2

* Pairwise differences are made between pre- and post-treatment estimates within a treatment. Means were considered statistically significantly different when $P < 0.05$, and are represented with a letter immediately after the estimates in the table

Table 3-3. Pre and Post comparison of Saplings per acre and Sapling Basal area

Response Variable	Control (n = 24)		Thin (n = 22)		Burn (n = 24)		Burn & Thin (n = 22)	
	2014	**2016**	**2014**	**2016**	**2014**	**2016**	**2014**	**2016**
	------------------------------------ **Saplings per acre** -------------------------------							
Total	234	198	262	209	200	153	**179 a**	**86 b**
Oaks	15	18	78	73	20	19	6	5
A. Elm	61	48	47	43	38	35	**62 a**	**30 b**
ERC	58	65	51	24	47	35	20	0
	------------------------------- **Sapling Basal area (ft^2/ac)** ------------------------							
Total	0.17	0.15	0.30	0.25	0.21	0.17	**0.19 a**	**0.08 b**
Oaks	0.03	0.03	0.10	0.09	0.02	0.03	0.05	0.04
A. Elm	0.05	0.04	0.08	0.09	0.04	0.04	0.03	0.03
ERC	0.05	0.05	0.05	0.01	0.02	0.02	0.01	0.00

* Pairwise differences are made between pre- and post-treatment estimates within a treatment. Means were considered statistically significantly different when $P < 0.05$, and are represented with a letter immediately after the estimates in the table

Table 3-4. Pre-and Post-comparison of Seedlings per acre

Response Variable	Control (n = 24)		Thin (n = 22)		Burn (n = 24)		Burn & Thin (n = 22)	
	2014	**2016**	**2014**	**2016**	**2014**	**2016**	**2014**	**2016**
	---------------------------------- **Seedlings per acre** ----------------------------------							
Total	2258	2539	**1608 a**	**3356 b**	1666	2403	1979	1693
Oaks	541	488	396	492	**349 a**	**709 b**	349	398
E. redbud	**746 a**	**1298 b**	**577 a**	**1750 b**	524	800	603	610
ERC	108	125	123	169	**103 a**	**0 b**	**119 a**	**7 b**

* Pairwise differences are made between pre- and post-treatment estimates within a treatment. Means were considered statistically significantly different when $P < 0.05$, and are represented with a letter immediately after the estimates in the table

Table 3-5. Canopy cover and understory vegetation measurements

Response Variable	Control (n = 10)		Thin (n = 10)		Burn (n = 10)		Burn & Thin (n = 9)	
	2014	**2016**	**2014**	**2016**	**2014**	**2016**	**2014**	**2016**
	---------- Percentage (%) ----------							
Canopy cover	86	89	90	79	86	85	87	84
Shrub cover	47	46	38	35	41	24	57	24
	---------- Inches (in.) ----------							
Understory Vegetation height	30.2	26.7	30.7	24.9	25.6	16.5	26.0	13.5

*Canopy cover and shrub cover variables were analyzed with the original discrete propotion responses. For better representation, the final lsmean values are presented as the percentage values

Chapter 4 - Prescribed Fire and Mechanical Thinning Effects on Fuel Loading in an Oak Dominated Woodland in the Forest-Prairie Ecotone of Kansas

Abstract

A 90-acre tract of oak dominated woodland north of Manhattan, Kansas is being used to study the effects of prescribed burning and mechanical thinning on oak regeneration. Experimental design is a 2 (burn) x 2 (thin) factorial with a repeated measures design. Burning and thinning treatments were administered in spring 2015. The objective of the study is to investigate the effects of mechanical thinning and prescribed fire on fuel loading (FL), in an oak-dominated woodland in the forest-prairie ecotone of Kansas. Two components of the fuel complex; dead and downed woody debris, and duff/litter profile were quantified following FIREMON sampling procedure. Destructive samples of understory vegetation and forest floor were collected as direct measures of biomass. The burn and thin (BT) treatment recorded significant vertical fuel consumption, and comparatively higher reductions in fine woody debris and total FL. These observations, along with higher fire scar heights, suggested that BT treatment consumed more fuel and burned more intensely compared to burn only treatment. The finer fuels consumed during the initial burn recovered successfully during the last two years. With additional fuel accumulation in fall 2017, the fuel beds would be ready to accommodate a second burn treatment in spring 2018.

Introduction

Distribution of woody vegetation within the North American forest-prairie ecotone is largely limited to thin bands of forests along lowlands and stream drainages (Danner and Knapp, 2001; Knight et al., 1994). Though many factors influenced the historical development of these forests in a fire-maintained landscape, Native American activity had the most profound effect (Abrams and Nowacki, 2008; Knapp et al., 2009; Middendorf et al., 2009). While the prairie landscape was maintained intact by fires with shorter mean fire return intervals (MFI), adjacent forest patches experienced surface fires periodically, with comparatively longer MFI. Hence, species composition and vegetation structure within these woodlands were significantly impacted by these periodic surface fires (Abrams, 1986; Abrams, 1992; Briggs et al., 2005; VanderWeide and Hartnett, 2011).

This historical fire regime was altered with European settlement of the Central Plains by myriad of means including active wildfire suppression, recommendations against burning as a land-management practice, land fragmentation, intensive agriculture and cattle grazing (Abrams, 1992; Middendorf et al., 2009). With reduced fire frequency and intensity, there has been substantial woody vegetation expansion into the surrounding grasslands over the last century (Abrams, 1986; Briggs et al., 2005; Danner and Knapp, 2001; Knight et al., 1994). Meanwhile, exclusion of fire from the system led the woodlands in this landscape to undergo a successional shift as well, similar to oak-dominated forests throughout the eastern forest biome (Abrams, 1986; Nowacki and Abrams, 2008). Mainly two oak species, bur oak (*Quercus macrocarpa*) in mesic sites and chinquapin oak (*Quercus muhlenbergii*) in more xeric sites dominate the forests in northeast Kansas (Abrams, 1986). Oaks are intermediate in shade-tolerance. Therefore, as the forests gradually develop into closed-canopy status after decades of fire-suppression, oaks in the regeneration pool are outcompeted by shade-tolerant, fire-sensitive, mesophytic species (Nowacki and Abrams, 2008; Schweitzer et al., 2016). In Kansas, this shift is mainly signified by hackberry (*Celtis occidentalis*) replacing bur oak in mesic sites, and eastern redbud (*Cercis canadensis*) threatening chinquapin oak in xeric sites (Abrams, 1992).

While re-establishing the historical fire regime within the prairie ecosystem has widely being acknowledged through research (Bowles and Jones, 2013; Ratajczak et al., 2016), use of fire for oak dominated woodland restoration within this region has not been systematically studied. In contrast, use of prescribed fire as a silvicultural tool for oak woodland restoration has been widely studied and applied in eastern deciduous forests (Brose et al., 2014; Dey et al., 2016). Therefore, this research project was initiated with the overarching goal of understanding the potential of using prescribed fire and mechanical thinning to encourage oak regeneration in the forest-prairie ecotone of Kansas.

"Mesophication" is a phenomenon commonly experienced by forests undergoing long-term fire exclusion, where cool, moist microclimatic conditions develop overtime under shaded understories. The resulting fuel-beds that develop under these shade-tolerant, fire-sensitive species are less-conducive to fire, and often have lower flammability, higher moisture-holding capacity, faster decay rates, and slower fire spread rates (Hammond and Varner, 2016; Kreye et al., 2013; Nowacki and Abrams, 2008). Therefore, re-introducing fire into these systems as a part of restoration efforts could be challenging. Fuel loading (FL) is an important measure that can be used to determine how well a particular area would react to a fire incident. It estimates the total amount of flammable fuel available within an area, and is often measured on dry weight basis (Weir, 2009). Therefore, understanding the current FL, its characteristics, and the initial effects of management interventions such as prescribed fire and thinning is critical for the long-term success of the restoration program. However, such effects are poorly studied in oak ecosystems, especially within the forest-prairie ecotone (Kolaks et al., 2004). Hence, the objective of this study is to assess the FL in an oak-dominated woodland in the forest-prairie ecotone of Kansas, and investigate the initial effects of an oak restoration effort with mechanical thinning and prescribed burning on FL and vegetation.

Methods

Study site and experimental design

A 145-acre tract of oak dominated woodland in Manhattan, Kansas (GPS location: 96 40'41.316"W 39 19'37.983"N) is being used for the study. As part of the Howe Natural Resources Education Center, the site is owned by the Department of Horticulture and Natural Resources, Kansas State University. The site is composed of a mix of upland oak and eastern redcedar (*Juniperus virginiana*) stands. However, the current research is limited to the oak-dominated portion of the property.

The study area was compartmentalized into 12 management units (compartments) ranging 6-10 acres in size (Figure 4-1). These compartments were grouped into three blocks, based on topography. Each block contains four compartments. The two-way factorial treatment structure has two levels of burn (burn and no-burn) and two levels of thin (thin and no-thin). Compartment boundaries often follow natural drainages to facilitate cost-effective establishment and management of fire breaks. The burn treatment was randomly assigned to a 2-compartment unit (whole-plot) within a block, whereas the other half (2-compartments) was left unburned. The 2-compartment units were further split into two 1-compartment units (split-plot) for the random assignment of the thinning treatment. Thus, the experimental units for burn and thin treatments were the whole-plot and split-plot, respectively. This assignment of treatments allowed four treatment combinations; “burn only” (B), “thin only” (T), “burn and thin combined” (BT) and a no treatment “control” (C) within each block. In total, 92 circular permanent data collection points were established (Figure 4-2) throughout the study area with a frequency of 1 plot per acre. Since there are multiple observational units (circular plots) within a compartment, they are considered as sub-sampling. At this stage of the study, FL has been sampled three times: pre-burn FL in spring 2015, FL immediately following the burn treatment in late-spring of 2015, and FL two-growing seasons post-treatment in spring 2017. Therefore, the overall experimental design for the study is a randomized complete block design in a split-plot with sub-sampling and repeated measures.

Treatments

The thinning treatment was conducted in January 2015 with a prescription of removing 25 trees per acre, mainly Eastern redcedar (ERC), American elm (*Ulmus americana*), hackberry, and Eastern redbud, and 50 saplings per acre of American elm, Eastern redbud, ERC and hackberry. Trees were single girdled while the saplings were completely cut and treated with a chemical mix of 25% Garlon mixed with diesel fuel to suppress re-sprouting.

A late-spring, dormant season prescribed fire was conducted in April 2015. Fire treatment was administered by the Kansas Forest Service. The four-month gap between the thin and burn treatments allowed the foliage of cut ERC trees to be dried enough to catch fire and burn vigorously. A 75-^{o}F air temperature was recorded at the time of ignition, with a 20-ft. wind speed of 4-6 mph and a 33% relative humidity.

Data collection

Out of the 92 circular plots established for the entire project, 40 circular plots (3 plots per compartment at minimum) were used for data collection. The “fuel load (FL)” sampling protocol of fire effects and monitoring system (FIREMON) (Lutes et al., 2006), was followed to sample two components of the fuel complex: dead and downed woody debris (DWD), and duff/ litter profiles. Measurements of DWD were conducted based on the planar intercept method (Brown, 1974). Four 75-ft. transects were established at each data collection point at four aspects: 90°, 330°, 270°, and 210°. Based on its diameter size class, the DWD were separately tallied in the standard fuel size classes of 1-hour (0.0 to 0.25 in.), 10-hour (0.25 to 1.0 in.), 100-hour (1.0 to 3.0 in.) and 1000-hour (greater than 3.0 in.) fuels. The finer fuel classes of 1-hr, 10-hr, and 100-hr are identified as fine woody debris (FWD), while the coarser DWD of 1000-hr fuels are recognized as coarse woody debris (CWD). These classes are also referred to as time-lag classes, as the classification is based on how each size class responds to changes in moisture. All the DWD that intercepts an imaginary sampling plane extending 6 ft. vertically above the ground were measured and recorded. Both 1-hr and 10-hr fuels were tallied along a 6-ft. segment of the transect, while 100-hr fuels were tallied along a 12-ft. segment. Both diameter and decay class were recorded for 1000-hr fuels, and was inventoried along a 60-ft. segment (Figure 4-3).

Litter/ duff profile was assessed at two points (45 ft. and 75 ft.) along the sampling plane. Depth of the litter/duff profile down to mineral soil, and proportion of litter depth within the litter/ duff profile were measured. Three measurements of dead fuel depth were also measured at three adjacent 1-ft wide vertical partitions at the end of each transect (Brown, 1974). Additionally, a 2.7 ft^2 (0.25 m^2) quadrat was used to collect a destructive sample of understory non-woody vegetation and forest floor. The entire volume of the forest floor within the quadrat down to the top of the mineral soil was collected. Once the samples were taken into the lab, the non-woody vegetation samples were separated into shrubs and herbaceous vegetation, while the forest floor samples were separated into duff, litter, 1-hr, 10-hr and 100-hr fuel classes. These samples were oven dried to a constant weight at 60 °C and the dry weights recorded.

The initial FL inventory was conducted only in the burned compartments (B and BT). Immediately after the burn treatment was concluded, the post-burn FL was measured in the same plots. In addition to FL, all the trees and saplings within 30 ft. from the plot center were assessed for burn scars and recorded the scar heights along with the species and diameter at breast height (dbh). Within the same time frame, FL data collection was conducted at T and C compartments as well. No further management treatments were applied for the next two growing seasons of 2015 and 2016 before carrying out the third FL assessment in the spring of 2017. This evaluation was intended to document on FL recovery after two growing seasons, which would help inform management decisions on thinning and prescribed burning in spring 2018. The understory vegetation sampling was conducted before leaf-fall in fall, and was done at two time points. The initial sampling was done in fall 2014, before performing the thinning and burning treatments, and the final sampling was done in fall 2016.

Data processing and statistical analyses

Data collected following the FIREMON sampling protocol (DWD and duff/litter profile) were organized, stored and processed using the FFI-Lite (FEAT/FIREMON Integrated) version 1.05.03.09 database management software tool (Lutes et al., 2009). The software constructs a summary report with average FL in tons per acre of each fuel component for each plot. It uses specific gravities and equations outlined in the handbook for inventorying downed woody material (Brown, 1974) for biomass calculations. This summary report was exported as a .csv file to be used in the statistical analyses. This transect-based data were organized into the following categories for statistical analysis: litter, duff, 1-hr, 10-hr, 100-hr, 1000-hr sound, 1000-

hr rotten, FWD (1-hr, 10-hr and 100-hr), DWD (FWD and 1000-hr), “litter and 1-hr” combined, “litter and DWD” combined, and total. Litter depth, duff depth, and total fuel depth were assessed separately as measurements of the vertical structure of the fuel complex. The quadrat-based fuel data were organized into the following categories: litter, duff, 1-hr, 10-hr, FWD, “litter and 1hr” combined, “litter, duff and FWD” combined, and the total (litter, duff, 1-hr and 10hr). The quadrat based sampling is unable to collect a good representative sample from 100-hr and above fuel classes. Hence, estimations were limited up to 10-hr fuels with this method. Non-woody understory vegetation data were classified as shrubs, herbs, and total non-woody vegetation. The quadrat based FL data were extrapolated to estimate the loadings in terms of tons per acre, to be comparable with the transect based estimates.

The fire scar height information was used to investigate the effects of B and BT treatments, different species categories, dbh size classes and economic value based category on fire scar heights respectively. These analyses were conducted after categorizing all the data into the following six species categories: All oaks, black walnut (*Juglans nigra*), bitternut hickory (*Carya cordiformis*), American elm, ERC, and “other” category, three economic-value based categories: high, moderate and low value, and four dbh based categories: 1 to 2.99 in., 3 to 4.99 in., 5 to 9.99 in., and > 10 in. Due to low abundance, hackberry, red mulberry (*Morus rubra*), eastern redbud, green ash (*Fraxinus pennsylvanica*), honeylocust (*Gleditsia triacanthos*) and Kentucky coffeetree (*Gymnocladus dioicus*) were clumped into the “other” category. All oaks species and black walnut were considered high value, while green ash, bitternut hickory and hackberry were categorized as moderately valued. The rest of the species were recognized as having low economic value.

Statistical analysis was conducted using the GLIMMIX procedure of SAS (version 9.4, SAS Inst. Inc.). Initial burn treatment effects were analyzed by comparing the pre-and post-burn data of 2015. This comparison was only conducted for B and BT treatment combinations. Therefore, this analysis was performed using a model of one fixed treatment effect with two levels: burn only (B), and burn and thin combined (BT). Then, the post-burn data for B and BT compartments along with T and C data for 2015, were compared with 2017 data to assess the FL recovery after two-growing seasons. The blocking factor was treated as the random effect with burn, thin, and time effects being treated as fixed effects in statistical models.

In each analysis, the studentized residual plots were checked for model assumptions, and accordingly either a gaussian or a lognormal distribution with an identity link function was employed. An appropriate description of the variances was utilized for heterogeneous residual variances. Finally, the best covariance structure was used based on the model-fit parameters. As an adjustment for the unbalanced nature of the dataset, the Kenward Rogers denominator degrees of freedom method along with Tuckey-Kramer adjustment for multiple comparisons were utilized in each model. Result interpretations were conducted based on the type III tests of fixed effects with concluding statistical significance at a P-value of < 0.05.

Results

Initial burn treatment effects on fuel loading

Quadrat-based, pre-and post-burn dry weight comparisons for litter revealed significant reductions with both B and BT treatments (Table 4-1). This decrease however was similar for both treatments and was driven by the significant time effect ($P < 0.01$). Averaged across the B and BT treatments, the estimated litter loading after the burn was 2.9 tons per acre lesser than the pre-burn condition. Throughout the analysis, a significant time by treatment two-way interaction effect would indicate that the two treatments (B and BT) have different effects on the response variable. On the contrary, having only a significant time effect as observed for litter suggests that the observed difference is attributable to the burn effect, irrespective of whether the treatment incorporates a thinning or not. Correspondingly, only the time effect was evident to be significant for 1-hr fuel and the combined category of "litter and 1-hr". Though 1-hr fuel reductions were not evident to be significant for the two treatments independently, the response averaged across the two treatments was found to be significant ($P = 0.04$). The combined "litter and 1-hr" FL averaged across the two treatments, reduced by an estimated 3.1 tons per acre with the burn, which was also evident to be significant ($P < 0.01$).

In contrast, a significant time by treatment two-way interaction effect was extant for duff ($P = 0.03$), 10-hr ($P = 0.03$), FWD ($P = 0.04$), and "total" ($P = 0.03$) fuel categories. When the thinning prescription was incorporated with the prescribed burn (BT), significant consumption of duff and FWD was indicated by having their dry weights being reduced by 59 and 56 percent ($P < 0.01$) respectively, compared to non-significant changes with B treatment. Concurrently, the BT treatment combination exhibited higher percent reduction of the total estimated fuel load (Table 4-1).

The transect-based FL assessment estimated additional components of the fuel complex such as the vertical structure and 1000-hr fuel, thereby collectively accounting for DWD. Similar to quadrat-based estimates, the treatment by time two-way interaction effect was not evident to be significant for litter, 1-hr, and "litter and 1-hr" fuel categories. Additionally, there was not enough evidence to support a significant interaction effect for duff, DWD, and "litter and DWD" components of the fuel complex. The significant time effect ($P < 0.01$) had caused the litter biomass to reduce significantly with both B and BT treatments. However, the estimated percent reduction was comparatively low (Table 4-2), compared to quadrat-based estimates (Table 4-1). On average, the initial burn had consumed 6 tons of litter per acre ($P < 0.01$), averaged across the B and BT treatments. Similar to the quadrat-based estimate, reduction of duff biomass was significant only within the BT treatment ($P = 0.02$). However, it was the significant time effect that drove this reduction, where an estimated 3.9 tons per acre of duff consumed by the burn, averaged across both B and BT treatments. The vertical profile of litter and duff had similar patterns of burn effects concomitantly with litter and duff FL (Table 4-2).

Estimates for FWD fuel components: 1-hr, 10-hr, 100-hr and total FWD demonstrated contrasting burn effects compared to quadrat based-estimates (Table 4-2). For 1-hr fuels, even though post-burn reduction was significant only for B treatment, it was the significant time effect responsible for this change ($P < 0.01$). On average, 0.08 tons per acre of 1-hr fuels were consumed by the initial burn treatment, averaged across B and BT treatment combinations. Changes in 10-hr fuel were insignificant with quadrat-based estimates. Nevertheless, the transect based estimate revealed a significant time by treatment interaction effect ($P = 0.03$). The B treatment caused the 10-hr fuels to be reduced by 0.4 tons per acre ($P = 0.02$), whereas the changes within BT treatment were not evident to be significant. In contrast to 10-hr fuel, it was the BT treatment that had caused significant reductions in 100-hr fuel ($P < 0.01$). Opposing effects observed with B and BT treatments on 1-hr, 10-hr, and 100-hr fuel categories independently, resulted in changes to be non-significant when their cumulative total (FWD) was considered (table 4-2). There was not enough evidence in support of a significant effect for FWD and “1000-hr sound” fuel components, with the type III tests of fixed effects. The time by treatment interaction effect was significant for “1000-hr rotten” fuel ($P = 0.03$). A significant time effect ($P = 0.03$) was revealed for the DWD category (1 to 1000-hr fuel). On average, 2.2

tons per acre of DWD was consumed by the initial burn, averaged across the B and BT treatments. Finally, the results demonstrated a significant time by treatment two-way interaction effect ($P < 0.01$) for total fuel load. Only the BT treatment had reduced the total fuel load (50%), with a statistical significance ($P < 0.01$). This outcome is supported by the estimates of changes in total fuel depth (Table 4-2), where a significant 6.7 in. reduction in total fuel depth was documented in BT data.

Fire effects on understory vegetation and tree/ sapling fire scars

A significant difference in average fire scar height was observed between B and BT treatments ($P < 0.01$). The mean fire scar height for BT treatment was 8.3 in., compared to 6.2 in. for B treatment (Table 4-3). However, the variability within BT treatment was higher, with measured fire scars ranging from 0 to 270 in. On average, species category with high economic value recorded fire scars that were 3.5 in. taller than the moderately valued species category ($P = 0.01$). Further investigation revealed tree species categories to be significant as well ($P < 0.01$). The mean scar height for black walnut (20 in.) was revealed to be significantly higher than for bitternut hickory (5 in.) and “other species” category (6.7 in.). However, fire scar height was not evident to be significant between dbh-based groups.

With regard to understory shrub vegetation, the three-way interaction effect between time, burn and thin was not evident to be statistically significant. However, the two-way burn by time interaction effect was statistically significant ($P = 0.04$). On average, the shrub vegetation biomass in 2016 was 37 g higher than the pre-treatment samples collected in 2014, averaged across the unburned plots (T and C). This difference was statistically significant ($P = 0.02$), in contrast to non-significant changes documented in the burned treatments (B and BT). It was the thin by time two-way interaction effect that was significant ($P = 0.02$) for herbaceous vegetation.

This effect showed herb biomass increased significantly within T ($P = 0.01$), and BT ($P = 0.03$) treatments (Table 4-4). On average, the herb biomass in 2016, was 17 g higher than the 2014 estimates, averaged across the thinned treatments (T and BT), whereas no significant changes were recorded across the treatments which didn't incorporate a thinning (B and C). Finally, for the total understory vegetation, time effect was that was significant ($P = 0.02$). Once treatment combinations are considered individually, only T treatment yielded a statistically significant increase in total understory dry weight ($P = 0.03$).

Fuel loading recovery

The time by burn two-way interaction effect was significant ($P < 0.01$) for quadrat-based litter recovery estimations. This was reflected by both B and BT treatments demonstrating significant increases in litter biomass (Table 4-5). The estimated litter loading in 2017, averaged across the B and BT treatments, was 2.6 tons per acre higher than 2015 estimates. In contrast, the litter loading in unburned treatments was not evident to be statistically significantly different. Similar results were obtained for fuel category combinations of; "litter and 1-hr", "litter, duff, 1-hr, and 10-hr", and total fuel load (Table 4-5). All these fuel categories revealed significant burn by time two-way interaction effects ($P < 0.01$). None of the treatment combinations displayed significant effects on duff, 1-hr, 10-hr, and FWD fuel components. However, the time effect was significant for 1-hr fuel category ($P < 0.01$). On average, the 1-hr FL increased by 0.32 tons per acre between the two years, averaged across all treatment combinations. The FWD, which is the combination of 1-hr, 10-hr and 100-hr fuels, revealed a significant time by burn interaction effect ($P < 0.05$). On average, FWD increased by 1.16 tons per acre between the initial assessment in 2015, and final assessment in 2017, averaged across burned treatments (B and BT).

Similar to quadrat-based litter recovery assessment, the time by burn two-way interaction effect was significant ($P < 0.05$) for transect-based litter assessment. Litter biomass averaged across the burn treatments (B and BT) increased by 3.6 tons per acre ($P < 0.01$) after two years post-burn. Data from the transect-based assessment showed a significant time by burn interaction effect ($P < 0.01$) that resulted in an significant increase in the duff biomass within B and BT treatment combinations to increase significantly (Table 4-6). Similar to what was observed with the initial burn effects, changes within the vertical structure of litter/ duff profile followed a similar pattern of treatment effects, similar to FL data. The three-way interaction effect between burn, thin and time fixed effects was significant for 1-hr fuel category ($P = 0.03$). Both B and T treatments yielded significant increases in 1-hr fuel category. None of the treatment combinations posed significant effects on 10-hr, 100-hr, 1000-hr solid, FWD and DWD fuel class combinations (Table 4-6). The time by burn interaction effect was again significant ($P < 0.01$) for "litter and 1-hr" combined category, which was reflected by B and BT treatments showing significant increases ($P < 0.01$). The BT treatment resulted in significant increases in total fuel loading. However, this change is attributable to the significant burn by time two-way interaction effect ($P < 0.01$), where the total FL increased by 7.1 tons per acre, averaged across the two burn treatments (B and BT).

Discussion

The litter and duff layers play an important role in a prescribed burn by enhancing fire continuity and also protects the soil by acting as a layer of insulation during a fire. However, the consumption of these two layers depends on fire behavior. Compared to duff, litter is less densely packed, with abundant air pockets, and has lower moisture and mineral content. Therefore, the litter layer is consumed during the flaming phase of the burn and maintains fire continuity, while the duff layer mainly gets consumed during the smoldering phase of combustion (Lutes et al., 2006). Both quadrat-and transect based estimations revealed that the litter layer was consumed similarly between B and BT treatments, with the BT treatment resulting in a higher impact on the duff layer. Simultaneously, the vertical structure of duff and total fuel depth was significantly reduced with the BT treatment, suggesting a significant vertical fuel consumption. Higher consumption of FWD was recorded with the BT treatment. Cumulatively, the BT treatment resulted in a greater percent reduction in total FL. The fire scar investigation revealed higher scar heights for BT. All these results suggest that the BT treatment consumed more fuel and burned more intensely compared to B treatment.

At the same time, it is necessary to understand contradictory observations reported in the study, where it was noticed that that 1-hr and 10-hr FL reductions was only significant for B treatment. This could be explained by the impact of thinning. In some plots it was visually observed that girdled trees, their branches, and thinned saplings had fallen onto the transects both after the pre-burn FL inventory, and during the fire. This resulted in increasing FL estimates for certain time lag classes, which was reflected by final results. Therefore, on top of natural fuel addition, the compartments which had a thinning treatment will continue to experience additional fuel accumulation over time.

Understory shrub and herb vegetation changes can be related to treatment effects on understory competition and light environments. Treatment effects on woody vegetation were studied separately, and are not discussed here. Overstory thinning enhanced the understory light conditions favoring the growth of certain species. The burn treatment top-killed most of the understory vegetation and the most competitive species demonstrated a vigorous re-growth, making full use of the enhanced light conditions through thinning. A similar response was observed in the shrub and herbaceous understory where thinning and unburned treatments resulted in higher herb and shrub biomass.

Information on the fuel recovery process provides vital information for the continuation of the restoration program. During the initial burn treatment, the finer fuel components experienced higher consumption, especially the litter, duff and FWD. However, these fuel components recovered during the next two years. Only litter FL and litter depth in B treatment, and “litter and 1hr” fuel category in both B and BT treatments had significantly different estimates between the initial and 2017 estimates. However, litter accumulation during fall 2017 would further increase the litter loadings in these compartments.

As mentioned before, proper recovery of the litter and duff layer before conducting another burn is vital, as it provides an insulation protection for soils, nutrients and soil biota from damaging temperatures. With the terrain present in the landscape, and the possibility of fuel movement downslope with wind and precipitation, we can assume that the initial FL in 2015 was the equilibrium fuel load for this site. Therefore, with successful FL recovery after 2 years, we can conclude that this site can reach its fuel load equilibrium within 2-3 years after a surface fire.

Within the analysis, some discrepancy between the quadrat and transect based estimations were observed. This is clearly evident with the estimations for litter (Figure 4-4 and 4-5), which could be attributed to the differences in respective methodologies. Within the transect method, the litter and duff layers were measured as a height of the litter/duff profile. However, environmental conditions such as after a precipitation event versus hot dry weather, would affect the compactness of the litter and duff layers, which in-turn would influence the accuracy of the height measurement. In contrast, a destructive sample is collected for the quadrat-based method, which was then used to measure the dry weight. Therefore, the quadrat-based estimations can be considered more accurate on estimating finer components of the fuel complex including litter and duff. However, the quadrat-based method is unable to collect a representative sample from 100-hr and above fuel classes. Therefore, we can conclude that the most effective approach for FL estimation is to use the two methods complimentarily.

The oak regeneration response study revealed successful oak regeneration following the initial treatments. However, some competitive species especially eastern redbud, re-sprouted vigorously as well. Hence, another burn treatment will be required to further suppress the competitors and provide a competitive advantage for oaks. Simultaneously, another overstory and mid-story thinning is necessary for the stocking rate to be reduced to a favorable range for oak regeneration. Considering positive fuel recovery, further litter accumulation in fall 2017, and a planned second thinning treatment in early spring of 2018, we can conclude that the burn compartments (B and BT) will be ready for the second burn treatment in late-spring of 2018.

As a final remark, this study revealed that the BT treatment has major implications with respect to tree scarring. Trees with high economic value, especially black walnut, were observed to have significantly taller fire scars, and dbh had no significant effect on scar heights. However, visual observations in the field revealed that scarring is highly dependent on fuel accumulation around trees after the thinning process. Often cut ERC trees were in close proximity to black walnut trees that recorded taller fire scars. This also has safety concerns as well, it is possible for thinned trees to act as ladder fuels and create a vertical fuel continuum from forest floor up to the crown. Therefore, it is recommended to be cognizant during the thinning process to avoid fuel accumulation around high-value trees.

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Figure 4-1. Study area delineated into 12 compartments

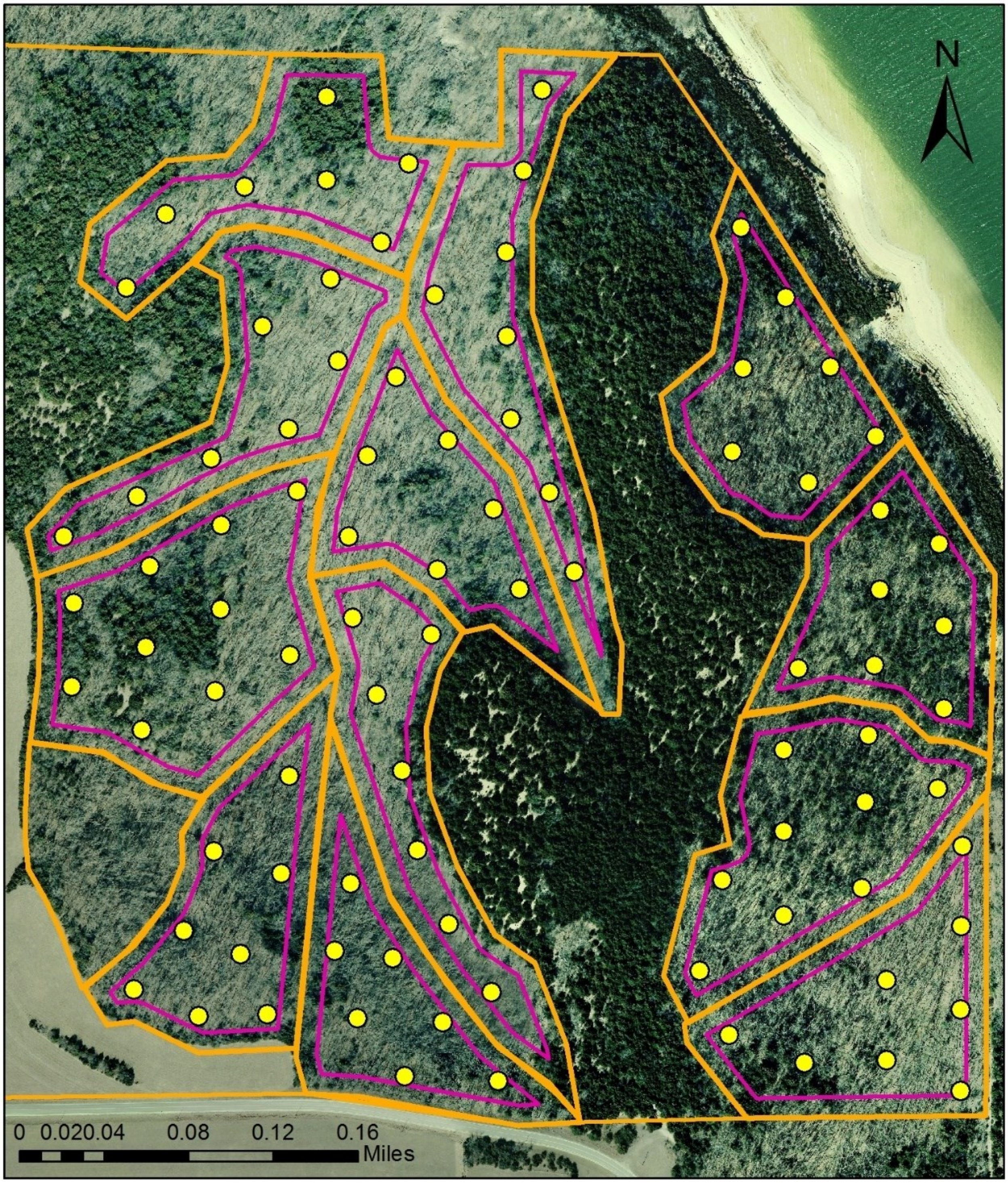

Figure 4-2. Permanent data collection points (circular plots)

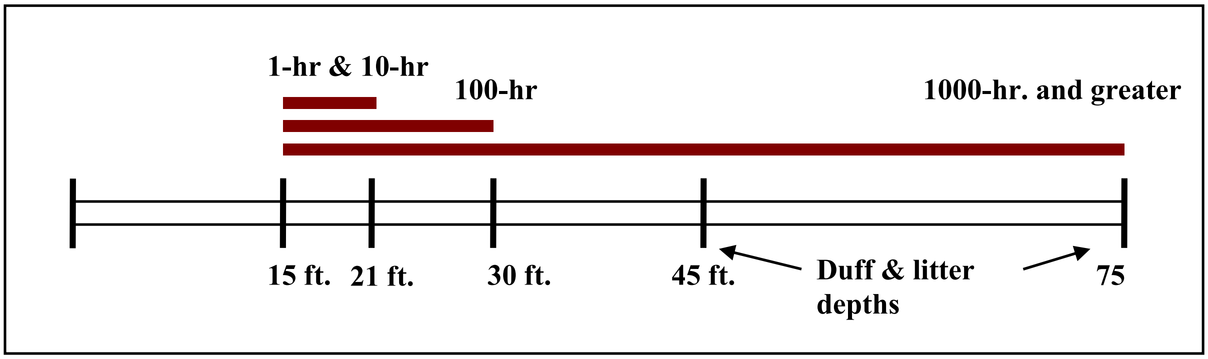

Figure 4-3. FIREMON sampling plane layout (1 transect) for FL estimation (Lutes et al., 2006)

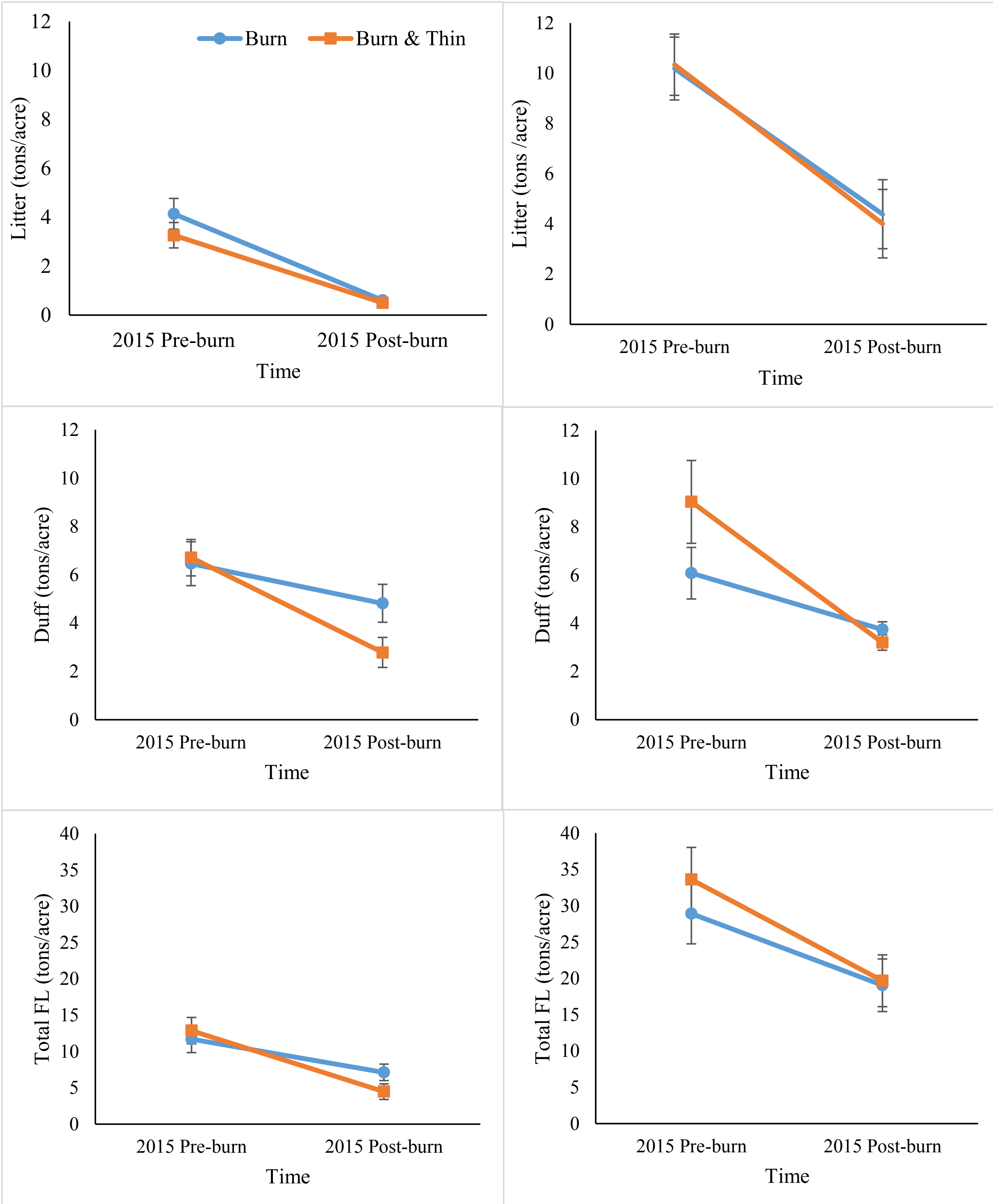

Figure 4-4. Quadrat based (left) and transect based (right) estimates on initial burn effects on litter, duff and total FL measured by the two methods

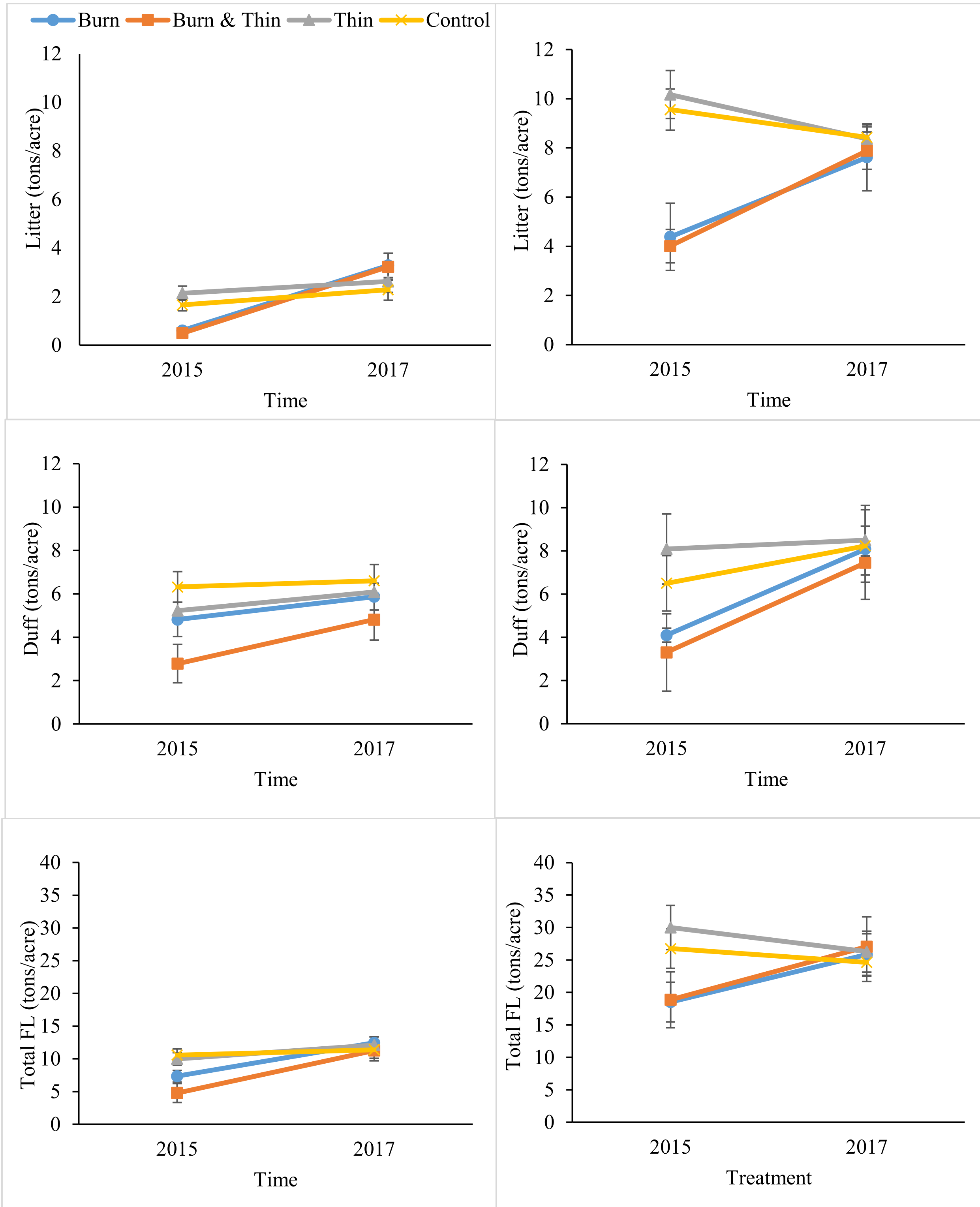

Figure 4-5. Quadrat based (left) and transect based (right) estimates on Fuel Load (FL) recovery with regard to litter, duff and total FL measured by the two methods

Table 4-1. Pre-and Post-burn fuel dry weights - Quadrat sampling

Fuel Category	Burn			Burn and Thin		
	Pre-burn	Post-burn	Percent reduction	Pre-burn	Post-burn	Percent reduction
	---- tons/acre ----		--- (%) ---	------- tons/acre ------		--- (%) ---
Litter (L)*	**4.14 a**	**0.61 b**	**85**	**3.27 a**	**0.50 b**	**85**
Duff (D)**	6.46	4.82	25	**6.71 a**	**2.78 b**	**59**
1hr*	0.79	0.52	34	0.82	0.62	24
10hr**	0.82	1.07	-30	1.37	0.68	51
FWD**	2.14	1.68	22	**3.09 a**	**1.36 b**	**56**
L and 1hr*	**4.64 a**	**1.20 b**	**74**	**3.94 a**	**1.12 b**	**72**
Total**	**11.69 a**	**7.12 b**	**39**	**12.87 a**	**4.46 b**	**65**

Means followed by a letter (a, b) are significantly different ($P < 0.05$). Bolded for emphasis

***Significant time effect:** Observed difference is due to the burn effect, irrespective of whether the treatment incorporates a thinning or not

****Significant time x treatment effect:** Different treatment by time combinations have different effects on the observed response variable

Table 4-2. Pre-and Post-burn fuel loading - Transect sampling

Fuel Category	Burn			Burn and Thin		
	Pre-burn	**Post-burn**	**Percent reduction**	**Pre-burn**	**Post-burn**	**Percent reduction**
			Fuel Loading			
	------- tons/ acre ------		--- (%) ---	------- tons/ acre ------		--- (%) ---
Litter (L)*	**10.2 a**	**4.4 b**	**57**	**10.3 a**	**4.0 b**	**61**
Duff (D)*	6.4	4.1	36	**9.3 a**	**3.3 b**	**65**
1hr*	**0.18 a**	**0.09 b**	**50**	0.20	0.13	35
10hr**	**2.0**	**1.6**	**20**	2.2	2.4	-9
100hr**	2.5	2.6	-4	**3.8 a**	**3.1 b**	**18**
1000hr sound	1.9	1.0	47	2.4	2.7	-13
1000hr rotten**	2.9	4.2	-45	4.3	2.7	37
FWD	4.8	4.2	13	5.9	5.8	3
DWD*	9.9	8.9	10	14.4	10.5	27
L and 1hr*	**10.4 a**	**4.5 b**	**57**	**10.6 a**	**4.1 b**	**61**
L and DWD*	**21.2 a**	**14.0 b**	**34**	**25.6 a**	**14.8 b**	**42**
Total**	28	19	32	**38 a**	**19 b**	**50**
			Vertical Structure			
	------- inches (in) ------		--- (%) ---	------- inches (in) ------		--- (%) ---
Litter Depth*	**2.1 a**	**0.9 b**	57	**2.1 a**	**0.8 b**	**62**
Duff Depth*	0.7	0.4	43	**0.9 a**	**0.4 b**	**56**
Fuel Depth**	6.4	3.4	47	**12.1 a**	**5.4 b**	**55**

Means followed by a letter (a, b) are significantly different ($P < 0.05$). Bolded for emphasis

*__Significant time effect:__ Observed difference is due to the burn effect, irrespective of whether the treatment incorporates a thinning or not

**__Significant time x treatment effect:__ Different treatment by time combinations have different effects on the observed response variable

Table 4-3. Fire scar analysis

Treatment	No. of trees assessed	No. of scarred trees	Percent scarred	Range of scar heights		Mean scar height	Median scar height	Standard error of the mean
				Low	High			
			- (%) -	------------------------ inches ------------------------				
B	379	174	46	0	36	**6.2b**	6.5	0.33
BT	241	140	58	0	270	**8.3a**	7.5	0.77

Means followed by a letter (a, b) are significantly different ($P < 0.05$). Bolded for emphasis

Table 4-4. Understory vegetation dry weights

	Burn		Burn & Thin		Thin		Control	
	2014	**2016**	**2014**	**2016**	**2014**	**2016**	**2014**	**2016**
	-- dry weight (g) -------------------------------------							
Shrubs	17	21	44	33	27	69	36	68
Herbs	19	29	**13 a**	**34 b**	**10 a**	**23 b**	20	22
Total	40	45	60	72	**41 a**	**85 b**	80	82

Means followed by a letter (a, b) are significantly different ($P < 0.05$). Bolded for emphasis

Table 4-5. Fuel load recovery - Quadrat sampling

Fuel Category	Burn		Burn and Thin		Thin		Control	
	2015	**2017**	**2015**	**2017**	**2015**	**2017**	**2015**	**2017**
	---------------- tons/acre ----------------							
Litter (L)**	**0.61 a**	**3.28 b**	**0.50 a**	**3.23 b**	2.14	2.62	1.66	2.28
Duff (D)	4.82	5.87	2.78	4.82	5.23	6.08	6.32	6.60
1hr*	0.52	0.91	0.62	1.12	0.84	1.18	0.89	0.96
10hr	1.07	0.95	0.68	1.21	1.41	1.66	1.28	1.23
FWD**	1.68	2.55	1.36	2.82	2.30	3.25	2.39	2.36
L & 1hr**	**1.20 a**	**4.12 b**	**1.12 a**	**4.30 b**	2.98	3.80	2.57	3.19
Total**	**7.35 a**	**12.45 b**	**4.78 a**	**11.26 b**	9.99	12.12	10.58	11.38

Means followed by a letter (a, b) are significantly different ($P < 0.05$). Bolded for emphasis

***Significant time effect:** Observed difference is due to the burn effect, irrespective of whether the treatment incorporates a thinning or not

****Significant time x burn effect:** Different burn by time combinations have different effects on the observed response variable

Table 4-6. Fuel load recovery - Transect sampling

Fuel Category	Burn		Burn and Thin		Thin		Control	
	2015	2017	2015	2017	2015	2017	2015	2017
	Fuel Loading							
	---------- tons/ acre ----------							
Litter (L)**	**4.4 a**	**7.6 b**	**4.0 a**	**7.9 b**	10.2	8.5	9.8	8.4
Duff (D)**	**4.1 a**	**8.8 b**	**3.3 a**	**7.7 b**	7.0	8.5	6.1	8.1
1hr***	**0.09 a**	**0.18 b**	0.13	0.16	**0.16 a**	**0.22 b**	0.13	0.16
10hr	1.5	2.2	2.4	1.8	1.8	1.7	1.5	1.2
100hr	2.6	2.1	3.1	3.4	1.9	2.3	2.3	1.8
1000hr sound	1.0	0.9	2.7	3.3	2.7	2.7	3.4	2.5
1000hr rotten	4.2	1.3	2.7	2.3	1.4	1.5	3.5	1.0
FWD	4.2	4.5	5.8	5.3	4.1	4.3	4.0	3.3
DWD	8.9	6.8	10.5	10.2	9.1	9.8	10.9	7.1
L and 1hr**	**4.5 a**	**7.8 b**	**4.1 a**	**8.0 b**	10.3	8.6	9.9	8.7
L and DWD**	14	15	15	18	20	18	21	16
Total**	19	25	**19 a**	**27 b**	28	26	27	25
	Vertical Structure							
	---------- inches (in) ----------							
Litter Depth**	**0.9 a**	**1.5 b***	**0.8 a**	**1.6 b**	2.0	1.7	2.0	1.7
Duff Depth**	**0.4 a**	**0.8 b**	**0.4 a**	**0.8 b**	0.8	0.8	0.6	0.8

Means followed by a letter (a, b) are significantly different ($P < 0.05$). Bolded for emphasis

***Significant time effect:** Observed difference is due to the burn effect, irrespective of whether the treatment incorporates a thinning or not

****Significant time x burn effect:** The different burn by time combinations have different effects on the observed response variable

*** **Significant time x burn x thin effect:** The different time x burn x thin combinations have different effects on the observed response variable

Chapter 5 - Monitoring the Effects of Eastern Redcedar Expansion on Deciduous Forests within the Forest-Prairie Ecotone of Kansas using Multi-temporal Landsat Images

Abstract

North America's midcontinent forest-prairie ecotone is currently exhibiting an extensive Eastern redcedar (ERC) (*Juniperus virginiana*) encroachment. Rapid expansion of ERC has major impacts on the species composition and forest structure within this region, and suppresses previously dominant oak (*Quercus*) species. In Kansas, the growing-stock volume of ERC increased by 15,000% during 1965-2010. Identification of areas exhibiting rapid ERC encroachment rates is essential for land managers to target control efforts. Therefore, the overarching goal of this study was to evaluate the spatio-temporal dynamics of ERC in the forest-prairie ecotone of Kansas, and understand its effects on deciduous forests. This was achieved through two specific objectives: i) characterize an effective image classification approach to map ERC expansion, and ii) assess ERC expansion between 1986-2017 in three study sites within the forest-prairie ecotone of Kansas, and especially expansion into deciduous forests. The analysis was based on satellite imagery acquired by Landsat TM and OLI sensors during 1986-2017. The use of multi-seasonal layer-stacks with a Support Vector Machines (SVM) supervised classification was found to be the most effective approach to classify ERC distribution with high accuracy. The overall accuracies for the change maps generated for the three study areas ranged between 0.95 (95 CI: $\pm$ 0.02) and 0.96 ($\pm$ 0.03). The total ERC cover increased in excess of 6000 acres in each study area during the 30-year period. The estimated percent increase of ERC cover was 139%, 539%, and 283% for Tuttle Creek, Perry Lake, and Bourbon County north study areas, respectively. This astounding rate of expansion had significant impacts on the deciduous forests where the conversion of deciduous woodlands to ERC, as a percentage of the total encroachment were, 48%, 56% and 71%, for Tuttle Creek, Perry Lake and Bourbon County north, respectively. These results strongly affirm that control measures should be implemented immediately to restore the threatened oak woodlands of the region.

Introduction

Vegetation communities in ecotones are vulnerable to alterations in species composition due to the combined effects of climate change and land management practices, since they are close to the limits of their natural ranges (DeSantis et al., 2011). Within the schema of ecoregion classification for the United States (Figure 5-1), the transitional region between heavily forested eastern US and the prairie grasslands of the Midwest is identified as the forest-prairie transitional region (Bailey, 1994; Johnson et al., 2009). This midcontinent forest-prairie transitional region/ ecotone of North America is currently experiencing an extensive Eastern redcedar (*Juniperus virginiana)* encroachment into the prairie ecosystem (Briggs et al., 2002a; Ratajczak et al., 2014). Eastern redcedar (ERC) continues to expand in area and density particularly in Missouri, Nebraska, Kansas, and Oklahoma. Simultaneously, it drives major alterations in species composition and forest structure in this region, suppressing the dominant oak (*Quercus)* species (DeSantis et al., 2011; Meneguzzo and Liknes, 2015).

In Kansas, the Forest Inventory and Analysis (FIA) data suggests that the growing-stock volume of ERC increased by 15,000% between 1965 and 2010 (Moser et al., 2013). Since 2.4 million acres of forest land constitutes only 5% of the state's total land base, the limited forested areas play an important role in providing habitats for wildlife and delivering many other ecological, economic and aesthetic benefits to the state. Oak/hickory is the predominant forest-type group in Kansas, accounting for 55% of the total forest lands (Moser et al., 2013). Continued fire suppression in forestlands and adverse effects of climate change such as prolonged drought would continue the current trend of shifting *Quercus*-dominated forests to *Juniperus*-dominated forests in this region and adversely affect associated ecosystem services

(DeSantis et al., 2011). Further, conversion of oak forests to ERC will intensify ERC expansion into the neighboring grasslands (Meneguzzo and Liknes, 2015).

Identifying locations where ERC expansion is occurring at rapid rates is essential for land managers to plan and manage control efforts (Meneguzzo and Liknes, 2015). Although ERC encroachment into the prairie ecosystem of the central US has been documented extensively (Briggs et al., 2002a; Briggs et al., 2002b; Ratajczak et al., 2016), the threat of ERC in driving a structural and species compositional change in deciduous forests is less commonly studied. Available literature on ERC expansion in the forest-prairie ecotone of Kansas has been focused on grasslands, and no multi-temporal study has been conducted on effects of ERC expansion on remaining woodlands of Kansas. Conducting a spatial analysis to identify locations where proactive management will be most effective has been identified as one of the research priorities for the control of ERC expansion in this region (Leis et al., 2017). The overarching goal of this study was to evaluate spatio-temporal dynamics of ERC expansion in the forest-prairie ecotone of Kansas, and understand its effect on deciduous woodlands.

Eastern redcedar is expanding in terms of area, density, and volume within the study region (Meneguzzo and Liknes, 2015). This observation was based on Forest Inventory and Assessment (FIA) data, a rigorous ground sampling inventory conducted periodically by the USDA Forest Service. However, extraction of spatial information and identification of hot-spots of ERC expansion is not facilitated with ground sampling-based inventories. In contrast, remote sensing image analysis provides vital information for resource management applications. Remote sensing essentially provides the best platform to conduct large-area, multi-temporal scale studies and it is being widely used in monitoring vegetation dynamics and land cover change detection (Homer et al., 2012; Lillesand et al., 2014; Sankey et al., 2010; Vogelmann et al., 2009).

Therefore, if a remote sensing-based approach can be employed to study ERC expansion, it will be possible to study vegetation dynamics over a broad geographic region and specifically identify locations experiencing rapid expansion rates.

Four categories of vegetation changes can be considered when using remote sensing for monitoring landscape changes: abrupt change, seasonal change, gradual ecosystem change, and short-term inconsequential change (Vogelmann et al., 2012). This study focuses on detecting "gradual ecosystem change", attributable to the invasive behavior of ERC. Therefore, image analysis and interpretation should eliminate other types of vegetation changes from interfering with the conclusion. The Landsat satellite mission provide a freely available, rich archive of systematically acquired multi-spectral imagery from 1972 up to the present, which can be used to assess and monitor natural resources (Vogelmann et al., 2012; Wulder et al., 2012). A fusion-based image classification method combining Landsat Thematic Mapper (TM) imagery with Light Detection and Ranging (LiDAR) data was used by Sankey et al. (2010) to study western Juniper expansion over a broad geographic region (southwestern Idaho). Making full use of the Landsat archive, Wang et al. (2017) mapped ERC encroachment into grasslands of Oklahoma, USA, through time series of Landsat Images and Phased Array L-band Synthetic Aperture Radar (PALSAR). However, both of these studies focused on grassland ecosystems, giving less attention to ERC dynamics around deciduous forests.

Being an evergreen tree species, ERC remains relatively constant in spectral characteristics throughout the year. Therefore, imagery acquired in the dormant season can be used to extract the ERC cover type from deciduous forests with high accuracy (Burchfield, 2014). Hence, by utilizing a time series of cloud-free, dormant season Landsat images spanning 2-3 decades, "gradual ecosystem changes" could be characterized. However, appropriate calibration and image processing techniques should be used prior to analysis, as the images are captured by multiple-sensors (e.g., TM, ETM+ and OLI) with different configurations and under varied atmospheric conditions.

Analysis of remote sensing imagery provides a powerful analytical tool for investigating landscape dynamics. But, accurate image classification can be challenging. Advancements made in modern data acquisition techniques and sensor technology have provided remote sensing analysts with vast quantities of data (Mennis and Guo, 2009). Due to the large size of data files, high dimensionality, and complexity, computationally efficient data mining algorithms and techniques are required to accurately convert these data into meaningful thematic information (Mennis and Guo, 2009; Mountrakis et al., 2011). The process of extracting useful information from vast quantities of data is called Knowledge Discovery in Databases (KDD), and the data mining step is only one critical step in the process of KDD (Fayyad et al., 1996). There are various pattern recognition or data mining techniques available for RS image classification. Therefore, in the process of KDD, the user needs to select the most effective data mining technique for accurate image classification.

The main objective of digital image classification is to categorize each object or individual pixel into separate information classes. However, these class labels may be known or unknown at the beginning. If the investigator has prior knowledge on the geography of the area and is able to identify all the information classes present in that area, a supervised image classification approach can be followed. If the investigator prefers to first identify the natural groupings in the data, and use this information to assign labels to separable classes, an unsupervised classification approach should be followed (Mather and Tso, 2009). In supervised classification, interactive "training areas" for each class are used for statistical assessment of class reflectance, and this evaluation is extrapolated to the whole image (Thomson, 1998). In this approach the analyst has more control over the process, yet needs to be knowledgeable about the area. In contrast, unsupervised classification locates a pre-selected number of cluster centers in the n-dimensional spectral space and iteratively move clusters until they obtain a maximum statistical separation (Thomson, 1998). Unsupervised classification has the advantage of reduced interaction time by the analyst, who nevertheless has less control over the resulting classes.

This study had the following two specific objectives: i) Characterizing an effective classification approach to map ERC expansion, by evaluating four image classification techniques: k-means clustering, ISODATA, maximum likelihood, and support vector machines (SVM), and three Landsat image preparation techniques: single-date layer stacks, multi-seasonal layer stacks, and composite layer stacks (multi-temporal/multi-year layer stacks); ii) Assess ERC expansion between 1986 and 2017 in three study sites within the forest-prairie ecotone of Kansas, and its effects on deciduous forests. The three study sites used in this study were selected based on current ERC distribution. With the abundant ERC distribution found in these locations, it enabled the analysis to go back in time and characterize expansion rates within the last 30 years using archival Landsat satellite imagery.

Method

Study area and dataset

To identify areas with high ERC distribution within the forest-prairie ecotone of Kansas, three cloud-free Landsat OLI images: scene path 28/row 33 (21st January 2017), path 27/row 33 (3rd March 2017), and path 27/row 34 (3rd March 2017) were downloaded from the United States Geological Survey EarthExplorer website (http://earthexplorer.usgs.gov). These three Landsat scenes cover the majority of the forest-prairie ecotone of Kansas (Figure 5-2). The images were selected from the dormant season for an accurate identification of the ERC cover type, as it is the most abundant evergreen tree species in the region. Images were displayed in a false color scheme: near infra-red (NIR), red, and green, and were mosaicked using “seamless mosaic” tool in ENVI 5.3 software. The mosaicked image was visually examined to identify areas with a wide ERC distribution. After careful inspection, three study areas; i) surrounding Tuttle Creek reservoir; ii) surrounding Perry Lake; and iii) Bourbon county north were selected (Figure 5-3). The study area surrounding the Tuttle Creek reservoir was used to assess different classification approaches. The main land cover classes in these selected sites were; water, wetland areas, grasslands, agricultural areas, deciduous woodlands, and eastern redcedar forests. None of the sites contained major cities, and all other urban features including roads and residential areas were hardly discernible in the 30-m medium resolution imagery. Hence, the urban land cover class was ignored in the analysis.

Data

Twelve cloud-free, Landsat Level-2 surface reflectance products were obtained through the USGS EarthExplorer website (Table 5-1). Images obtained for the initial time period for 1986-1988 were acquired by Landsat-5 Thematic Mapper (TM) sensor, while the recent imagery for 2015-2017 were acquired by the Landsat-8 Operational Land Imager (OLI) sensor. There are major differences between the sensors and image products. However, the 30-m spatial resolution remains the same for the spectral bands used in this study. The Level-2 surface reflectance products were atmospherically corrected, which were generated from Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) for Landsat TM images, and Landsat Surface Reflectance Code (LaSRC) for Landsat OLI images. This processing ensures higher consistency and comparability between images taken at different time periods, compared to level-1 digital number imagery (Masek et al., 2006; Vermote et al., 2016). Thus, it eliminates the requirement for additional pre-processing.

Characterizing an effective classification approach

Initially, the four classification methods were evaluated based on their classification accuracies of two single-date Landsat layer stacks for the study site surrounding Tuttle Creek reservoir (Figure 5-4). Spectral bands 1-5, and 7 of Landsat TM images were stacked using layer stacking tool of ENVI 5.3, and generated a TIFF image for 1986. For the 2017 image, the spectral bands 2-7 of Landsat OLI image were stacked. Each classification approach was expected to classify the two images with six land cover classes; grasslands, agriculture, ERC, deciduous woodlands, water, and wetlands. The following section provides a brief description of the respective classification approach. Image classification was performed using ENVI 5.3 software.

K-means clustering algorithm

K-means clustering is an unsupervised classification technique. The end goal of *k*-means algorithm is to find the optimal division of *n* entities in *k* groups. First, the algorithm must determine the initial number of clusters present in the data, and then locate the cluster means within the feature space. Within the process, each pixel is associated with the nearest cluster center using the euclidean distance (Mather and Tso, 2009). Based on the allocated pixels, the cluster means are re-calculated. This migration of cluster means is done iteratively until an optimal solution is reached where cluster means no longer change, or change from one iteration to another is less than a pre-defined threshold (Mather and Tso, 2009). This iterative process reaches a cluster solution with high intra-class similarity and low inter-class similarity, and each data point can only be in one cluster.

K-means unsupervised classification tool was used to perform the clustering. Maximum number of classes and iterations were set to 10 and 20 respectively. This allowed the clustering to occur until it converged. The classified images were manually inspected against the original Landsat image and an image with a higher resolution. Google Earth TM (http://earth.google.com) images and National Agriculture Image Program (NAIP) imagery were downloaded though the USDA geospatial data gateway (https://datagateway.nrcs.usda.gov), and were used to inspect the 1986 and 2017 images along with the original Landsat images. Each of the ten classes were assigned to one of the six land cover classes mentioned earlier, to generate the final classified images (Figure 5-5).

ISODATA

ISODATA is another most widely used unsupervised clustering algorithm, which is similar in most ways to *k*-means clustering algorithm. In both *k*-means clustering and ISODATA, the objective is to minimize the mean squared distance from each data point to its nearest centroid (cluster center). However, the significant advantage of ISODATA over *k*-means method is its ability to alter the number of clusters by deleting small clusters, merging nearby clusters, or splitting large diffuse clusters without user intervention (Memarsadeghi et al., 2007). The same sequence of steps as in k-means clustering technique was employed using ISODATA unsupervised classification tool of ENVI. Maximum number of classes was set to 10 with a minimum of 5. The change threshold was set at 5% and the minimum pixels per class to 1000. The initial clustering output generated 10 clusters, and these clusters were combined appropriately to generate the final classified image (Figure 5-6).

In contrast to unsupervised classification, supervised classification requires the user to select training areas from the data, for each pre-defined information class (Mather and Tso, 2009). Classification accuracy of this approach is highly dependent on how well the user defines these training areas. The training dataset is used to estimate the parameters of the classifier, and how well these parameter estimation is done will influence the overall accuracy of the final image classification (Charaniya et al., 2004). Since selection of accurate training sites is crucial, the analyst should be extremely knowledgeable about the area. Though selection of training sites is a tedious task, supervised classification is still preferred over unsupervised methods since it gives more accurate class definitions and high classification accuracy (Mather and Tso, 2009).

Maximum likelihood

In this procedure, the probability of each pixel belonging to one of each pre-defined set of classes is calculated using the mean and variance of each training class. This will create contours of probabilities around means of training data classes, and the unknown pixel will be placed in most probable class based on the contours (Mather and Tso, 2009). Since this classification is based on mean and variance of the training sample, the training data sample should be large enough to represent the variance of that class throughout the image. Maximum Likelihood supervised classification tool of ENVI was employed for this classification. The pre-defined training areas were selected to train the algorithm and to conduct the classification (Figure 5-7).

Support vector machines (SVM)

Support Vector Machines (SVM) is a supervised non-parametric learning technique (Mountrakis et al., 2011). It represents a group of theoretically superior machine learning algorithms which locates the optimal boundaries between classes in a feature space (Huang et al., 2002). In its simplest form, SVMs are linear binary classifiers which classify observations into one of the two possible labels by defining the optimal boundary between the two classes. At three dimensions this boundary becomes a plane, and with increasing number of variable dimensions, the separator becomes a hyperplane. The SVM classification tool of ENVI was used to perform the classification with a radial basis function as the kernel type. Default model specifications of: a gamma value of 0.143, a penalty parameter of 100, and a zero-probability threshold were used in the classification. The same training samples used for the MLC were used in the classification and to generate the final six-class classified image (Figure 5-8).

Multi-seasonal layer stacking with SVM

As an evergreen tree species, the spectral reflectance of ERC remains relatively constant throughout the year, compared to other vegetation in the landscape. Presence of other photosynthetically active vegetation in the surrounding area, such as winter wheat during the dormant season, and grasslands, deciduous forests, and agricultural lands during the growing season might create confusion with the ERC cover type, when a single-date image classification is employed (Burchfield, 2014). Therefore, the idea of using a multi-seasonal image stack is to allow the classification algorithm to utilize the relatively constant spectral reflectance of ERC to distinguish it from other vegetation demonstrating a fluctuating reflectance signal. Combining two images from the dormant season and growing season to create a multi-seasonal stack was found to be more effective in classifying the ERC cover (Burchfield, 2014).

Multi-seasonal image stacks were generated for 1986 and 2017, by layer stacking the dormant season image with a growing season image for the two study periods respectively (Table 5-1). A SVM classification was performed for the two multi-seasonal image stacks, using the previously created training areas (Figure 5-9). Post-classification inspection suggested that certain misclassifications can be avoided through improving the training area selection procedure. In this region, it is common to see burnt grasslands and fallowed agricultural lands that are not in production during the season of interest. Therefore, two additional classes: burnt areas and fallowed agricultural lands, were trained. However, once the classification was completed, fallowed agricultural lands and burnt areas were clumped into the agriculture and grassland classes respectively, to generate the final classification images (Figure 5-10).

Composite/multi-temporal image analysis with SVM

Combining all the images from different time points into a multi-temporal dataset to classify change classes, is known as a type of composite image analysis. This method was successfully used with Landsat satellite images and a SVM classification, to monitor the invasion of an exotic tree species from 1986 to 2006 in Argentina (Gavier-Pizarro et al., 2012). The advantage of this method is that it requires only one classification image for the entire study period to depict the spatial pattern of change.

The composite image for the Tuttle Creek study area was constructed by layer stacking dormant season Landsat images for four time periods: 1986, 1996, 2006, and 2017. Training areas were selected for seven classes: ERC cover in 1986, changed to ERC during 1986 to 1996, changed to ERC during 1996 to 2006, changed to ERC during 2006 to 2017, deciduous forests in 2017, other vegetation, and water. Gradual expansion of the ERC cover across the landscape is clearly visible with the final classified image (Figure 5-11). However, the selection of training areas for change classes is a very time consuming task, especially when support data such as imagery with higher resolution is not available.

Accuracy assessment

The accuracy assessment for the classification was conducted using a common reference dataset, as it would allow comparisons to be made across different classification approaches. The complete workflow is specified in appendix E. The reference dataset was created as a shapefile in ArcGIS 10.5, with 75 points per class. Classified images were imported into ArcMap as a shapefile, and converted to a raster along with the reference dataset. The two raster datasets of the reference and classified maps, were combined using the spatial analyst tool. The resulting table was used to construct the confusion matrix and compute user's accuracy, producer's accuracy, overall accuracy, and kappa coefficient.

Assessing ERC expansion between 1986-2017

The use of multi-seasonal layer stacks with SVM classification was concluded to be the most effective approach to classify the 1986 and 2017 images for the three study areas. Each image was classified using the method outlined in section "multi-seasonal layer stacking with SVM". Once the 1986 and 2017 images were classified in ENVI 5.3., they were converted to an ArcGIS compatible format. In ArcMap, these images were converted to a raster file format for further processing. A class score was assigned to each land cover class of the two classified images (Table 5-2). Using the new class score attribute as the value field, the 1986 image was subtracted from 2017 image with raster calculator tool. The resulting map consisted of 16 change classes. Hence, the reclassification tool was used to reclassify the map (Table 5-3), and construct the final change map for each study area with six change classes; i) deciduous to ERC, ii) non-forest to ERC, iii) ERC lost, iv) ERC stable, v) deciduous stable, and vi) all other. The non-forest to ERC category includes conversion of agricultural lands, grasslands and water/wetland areas into ERC dominated areas. The detailed workflow for constructing the change map is presented in appendix E.

Accuracy assessment and area estimation

The protocol used for accuracy assessment and area estimation followed the recommended good practices for map accuracy assessment and area estimation in land change studies (Olofsson et al., 2014). This statistically robust methodology is based on three pillars: i) stratified random sampling design for the selection of a subset of pixels from each class of the classified image; ii) an accurate reference dataset, which could label each unit in the sample with high accuracy; and iii) analysis of data using confusion matrices, and quantify errors in classification with estimates of overall accuracy, user's accuracy (commission error), and producer's accuracy (omission error). The strength of this methodology is that it incorporates the estimated errors in classification in estimating area of change. The final estimations are reported along with computed uncertainties in terms of confidence intervals.

The total area of different land cover classes in all three study areas were highly variable. Therefore, a stratified random sampling procedure was followed for the selection of samples from each class. Landsat satellite imagery along with high resolution NAIP and GoogleEarth™ imagery were used to gather reference information. The complete procedure from sample size determination to final area estimations followed the good practices guidelines (Olofsson et al., 2014).

Results

Selecting the most effective classification approach

The initial comparisons between classification techniques were conducted using single-date Landsat layer-stacks for the study area surrounding Tuttle Creek reservoir. The two unsupervised techniques, k-means clustering (Figure 5-5) and ISODATA (Figure 5-6), demonstrated major discrepancies in its classification solutions, compared to the supervised techniques of MLC (Figure 5-7), and SVM (Figure 5-8). Clearly, the unsupervised solutions failed to

classify the wetland land cover class, as it was misclassified as other vegetation. This is reflected in their respective error matrices (Table 5-7). In contrast, the supervised classification permitted selection of a training sample from wetland areas, which ultimately reduced misclassification error. The overall accuracy of classification for the two unsupervised techniques were less than 0.50, whereas the supervised classification solutions achieved higher accuracies between 0.84 to 0.91. Hence, supervised classification was preferred over unsupervised classification.

The solutions derived through the MLC (Table 5-6) and SVM (Table 5-7) classifications were comparable to each other. Misclassifications were recorded for deciduous forests with wetlands and agricultural lands, which were common to both MLC and SVM classifications, and more pronounced with the 1986 image. This caused the user's accuracy for deciduous forests in the 1986 classified image to be drastically reduced, and with the MLC solution it was around 61%. There was little difference between MLC and SVM classification solutions at this point. However, they have major differences with respect to their functionality. MLC requires normality in the dataset, whereas SVM is a non-parametric statistical learning technique. Within this study, it is not guaranteed that the dataset will follow a normal distribution. Additionally, SVM has the capability of attaining a higher classification accuracy even with a limited training sample (Mountrakis et al., 2011). Thus, due to its functional superiority, SVM was chosen as the classification technique best suited to this study.

The selected SVM classification method was employed to classify the two multi-seasonal images for 1986 and 2017 respectively (Figure 5-9). The corresponding error matrices revealed a slight improvement over single-date image classification (Table 5-8). The same multi-seasonal images were classified again after following an improved training area selection process. Result of this improved classification approach (Figure 5-10) yielded the best accuracy estimates achieved thus far (Table 5-9). Overall accuracies and Kappa coefficients for both 1986 and 2017 image classifications were between 0.93 and 0.96. This approach minimized misclassification errors. User's accuracy for deciduous forests were 88% and 94% for 1986 and 2017 images respectively. This is a vast improvement compared to previous solutions.

Finally, a composite image classification was conducted using SVM technique. The final change map derived through the composite analysis depicted the spatial pattern of ERC expansion over the years (Figure 5-11). However, the selection of training areas for change classes is a tedious process. There was much confusion even within a single change class, as one pixel area represents three decades of change. However, the advantage of this method is the same richness of information in the composite stack of image layers (Gavier-Pizarro et al., 2012). Identifying pixel trajectories before 2003, was highly complicated due to the unavailability of images with higher resolution such as NAIP imagery. This was experienced at both training and accuracy assessment stages. Due to its time consuming approach and complexity of the composite image analysis procedure, the previously characterized multi-seasonal image classification with SVM was concluded as the most effective classification approach for this study.

ERC dynamics within the three study regions

Tuttle Creek Reservoir

Visual comparison of the two classified images for 1986 and 2017 (Figure 5-12), clearly illustrates ERC expansion within the study area. The final change map (Figure 5-13) further dissects land cover change and ERC expansion based on its trajectory of change. Areas that were originally classified as deciduous forests in 1986 and were classified as converted to ERC in 2017, are depicted in black color. All other land cover classes that went through a similar conversion to become ERC dominated by 2017 are represented in pink color. The change map demarcates the areas with lost ERC cover during the study period, as well as stable ERC and deciduous forest stands. All other change and stable classes were clumped together since it's beyond the interests of this study.

A relatively small portion of the study area (Table 5-10) is covered by the two classes representing ERC expansion (deciduous to ERC and non-forest to ERC). Grasslands and agricultural lands dominates this landscape, a situation common throughout the forest prairie ecotone, and is represented by the change class of "other" in this map. Due to this high variability in total area per each change class, the error matrix for the change map is recommended to be reported in terms of area proportions (Table 5-11) (Olofsson et al., 2014). The estimated area proportions for each change class was used to estimate area, user's accuracy, producer's accuracy, and overall accuracy along with estimations on uncertainty (Table 5-12).

The overall accuracy of the change map was estimated to be 0.96 (95% CI: $\pm$ 0.02) (Table 5-12). User's accuracy and producer's accuracy for all the classes were above 80%, except for non-forest to ERC producer's accuracy. This suggested that a fair amount of ERC expansion into non-forest classes were not documented in the classified image. This is reflected by non-forest to ERC change class having a 95% confidence interval of around 2000 acres for change area estimation. However, a higher level of precision in classification is observed for other classes. In total, ERC cover has expanded into surrounding areas by about 8200 acres. If lost ERC area is taken into the account, it was estimated that the ERC cover around the Tuttle Creek reservoir has increased by around 6600 acres within the last 30 years (Table 5-19). The rate of increase is estimated to be a staggering 220 acres per year. Nearly a half of its expansion occurred into the deciduous forests, therefore it is quite evident that similar to grassland ecosystems, the deciduous woodlands in this area are affected by ERCs' rapid expansion.

Perry Lake

Similar to the area surrounding the Tuttle Creek reservoir, ERC expansion within this study region was clearly visible with the two classified images (Figure 5-14). ERC cover was not prominent in the 1986 classified map, but exhibited widespread distribution by 2017. This is evident by having a negligible proportion of area for ERC stable class in the final change map (Table 5-13). An estimated 99% of the ERC cover mapped in 2017 seemed to have developed after 1986. Representations in the final change map (Figure 5-15), were similar to the map constructed for Tuttle Creek.

The estimated overall accuracy of the change map was 0.96 (95% CI: $\pm$ 0.02). The producer's accuracy for change classes of non-forest to ERC and ERC lost were around 70% (Table 5-12). The margin of error was equal or in excess of 50% for these two classes. However, other classes were classified with a higher precision. In this study, our main focus lies on the change class of deciduous forests to ERC, which was classified with higher accuracy. The study area has experienced an ERC expansion of 7600 acres within the period of 1986 to 2017, of which a majority (56%) of the expansion occurred into the deciduous forests. The annual rate of ERC expansion within this region was estimated at 216 acres per year, after accounting for lost ERC cover during the same time. Yet again, the astounding rate of ERC expansion within this region is evident with significant impacts on the deciduous forests.

Bourbon County North

Similar to other two study regions, ERC expansion is clearly evident with the two classified images for 1986 and 2017 (Figure 5-16). ERC dominated areas can be observed in 1986 at the northeast section of the study region. After 30-years, ERC show a widespread distribution throughout the study area. The final change map (Figure 5-17) illustrates the spatial trajectories of this ERC expansion, where areas represented in black has undergone a conversion from deciduous forests to ERC by 2017. The pink colored areas represents ERC expansion into other cover types including grasslands and abandoned agricultural lands.

The overall accuracy of the change map was estimated at 0.95 ($\pm$ 0.03). Compared to previous two change maps, a higher producer's accuracy is observed for all the change classes associated with ERC cover (stable, lost and gained). The margin of error which is an estimate of the uncertainty as a proportion of the estimated total area was below 20% for all the classes. The estimated total gain of ERC cover within the 30-year period was about 6500 acres, out of which 71% symbolizes deciduous forest conversions. Once lost ERC cover is taken in to the account, the annual rate of expansion of ERC within this region is estimated at 202 acres per year. These observations are comparable with the results obtained for other two study regions.

Discussion

It is conclusively evident that ERC has expanded at an alarming rate within all three areas investigated in this study. The rate of expansion exceeded 200 acres per year in all three sites, and the percent increase of ERC cover ranged from around 140% to 540% (Table 5-19). This astounding rate of expansion of ERC cover was also evident to be having a major impact on the deciduous forests of the region. This is clearly illustrated by Figure 5-18, which depicts total estimated ERC encroachment for the three study areas, broken by its impact on deciduous forests and non-forest classes. Conversion of deciduous woodlands to ERC, as a percentage of the total encroachment were 48%, 56% and 71%, for Tuttle Creek, Perry Lake and Bourbon County north study areas, respectively. Eastern redcedar encroachment into the deciduous woodlands as a percentage of existing deciduous woodlands for the three sites were 25%, 13% and 18% respectively.

All three study regions, are located around recreational areas such as reservoirs, lakes, and state parks, and includes large number of rural homeowners. The underlying cause for the observed high ERC expansion could be related to how these lands are managed. ERC is commonly controlled in grasslands through the use of repeated prescribed burns. Nevertheless, most of these lands including ranches, land belong to rural landowners, and some government lands are not managed actively with frequent prescribed fires. Therefore, it provides conducive environments for ERC to expand into surrounding grasslands, deciduous forests, and abandoned agricultural lands. With continued fire exclusion, ERC gradually expands in area and density. In Kansas, a trend of ERC expansion, in disturbance-free environments was outlined through FIA inventory data (Moser et al., 2013). Further, once ERC starts invading deciduous forests, they have the ability to reduce the fitness of dominant oak species and facilitate ERC growth through positive soil-microbial feedbacks (Williams et al., 2013). This provides a plausible explanation for the observed ERC expansion into deciduous forests as documented in this study.

Pixel-based image classification of land cover with mixed vegetation is challenging (Wang et al., 2017). A crucial task in this study was to distinguish ERC cover from deciduous woodlands and other vegetation. The study was based on dormant season Landsat imagery which helped identifying the ERC cover, as it is the only native evergreen species in the region. A possible complication in this approach is that it might classify a pixel as ERC, even when it actually exists underneath a deciduous canopy which is not detected with leaf-off, dormant season imagery. Even if this error holds true, still the observations of ERC expansion and interpretations are valid since the change detection comparisons were made at pixel level. Any pixel that was classified as "converted to ERC by 2017" resembles areas that did not have ERC even in the understory in 1986. This highlights the importance of conducting the accuracy assessment on the final change map, instead of the individually classified maps for a single time point as it does not quantify the accuracy for change classes (FAO., 2016). However, in this study we used multi-seasonal layer stacks instead of single-date imagery. Multi-seasonal imagery proved to be more effective in classifying land cover in this region with high accuracy. The strength of multi-seasonal imagery is that it incorporates information from leaf-on, growing season image with leaf-off dormant season image at individual pixel level. Therefore, when a pixel is classified into a certain change class, the decision is made based on its spectral reflectance both in the dormant season as well as the growing season.

Despite the negative impacts on certain ecosystems, ERC is considered an important component of windbreaks across the region (Strine, 2004). Its dense, compact foliage, and rapid growth rates make ERC an excellent species to be used in windbreaks to protect crops, shelter livestock, and reduce wind erosion. Therefore, it is vital to acknowledge its importance, while managing ERC encroachment in this region. Accurate information on ERC distribution should become available for land management decisions to be made, especially when rapid expansion is evident.

This study focused on three study regions which demonstrated high ERC cover in 2017. This allowed us to go back in time and characterize the development of the current ERC cover during the past 30-year period. Therefore, it is understandable that the same rate of expansion of ERC is not experienced throughout the forest-prairie ecotone. The objective of this study was to investigate if ERC expansion has a significant impact on the deciduous forests of this region. This can only be studied by investigating the historical land cover dynamics. To the best of our knowledge, this is the first study which investigated ERC expansion effects on deciduous forests using a RS based methodology in this region. Results of this study strongly supports the FIA inventory based predictions on possible future alterations in species composition in this region (Meneguzzo and Liknes, 2015). Therefore, the lesson learned in this study strongly affirm that the remaining deciduous woodlands of this region should be managed with appropriate silvicultural techniques such as prescribed burning and mechanical thinning to reduce future ERC dominance.

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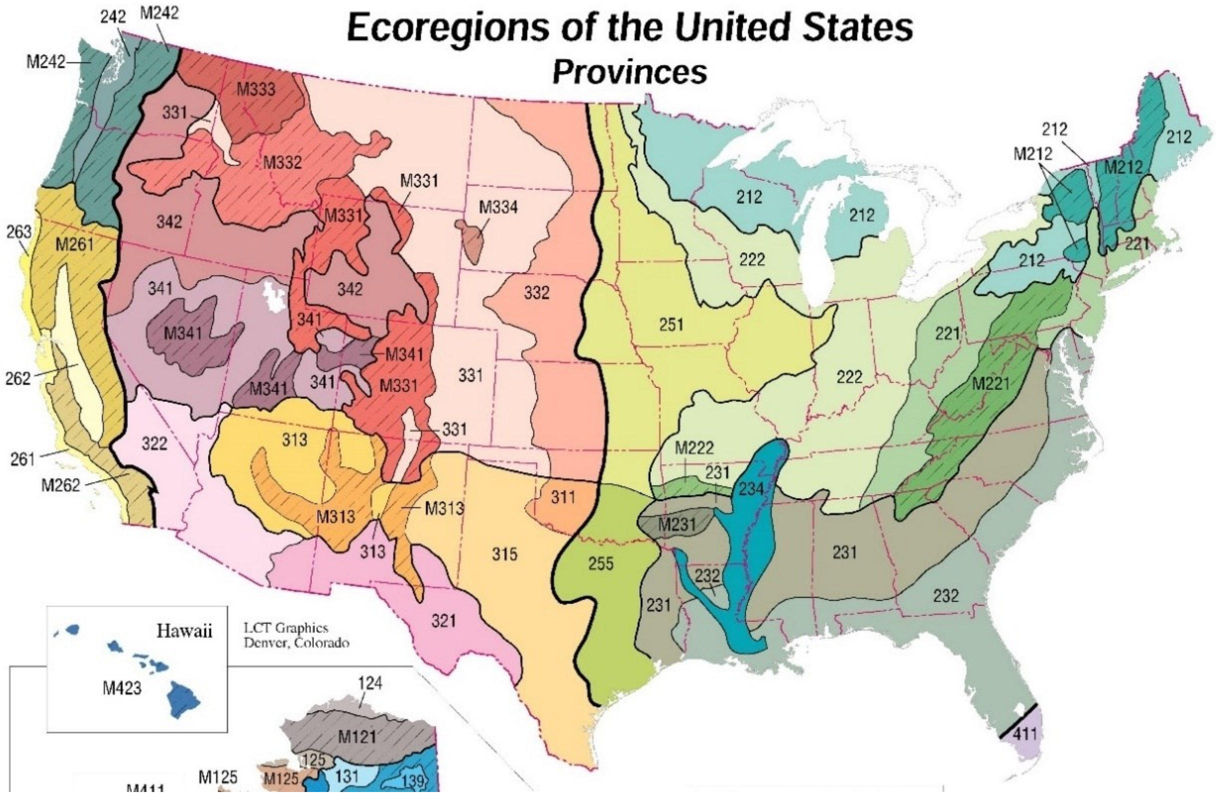


Figure 5-1. Ecoregions of the United States: The region corresponded by 251 (prairie parkland province - temperate) and 255 (prairie parkland province – subtropical) together represents the forest-prairie transitional region (Bailey, 1994)

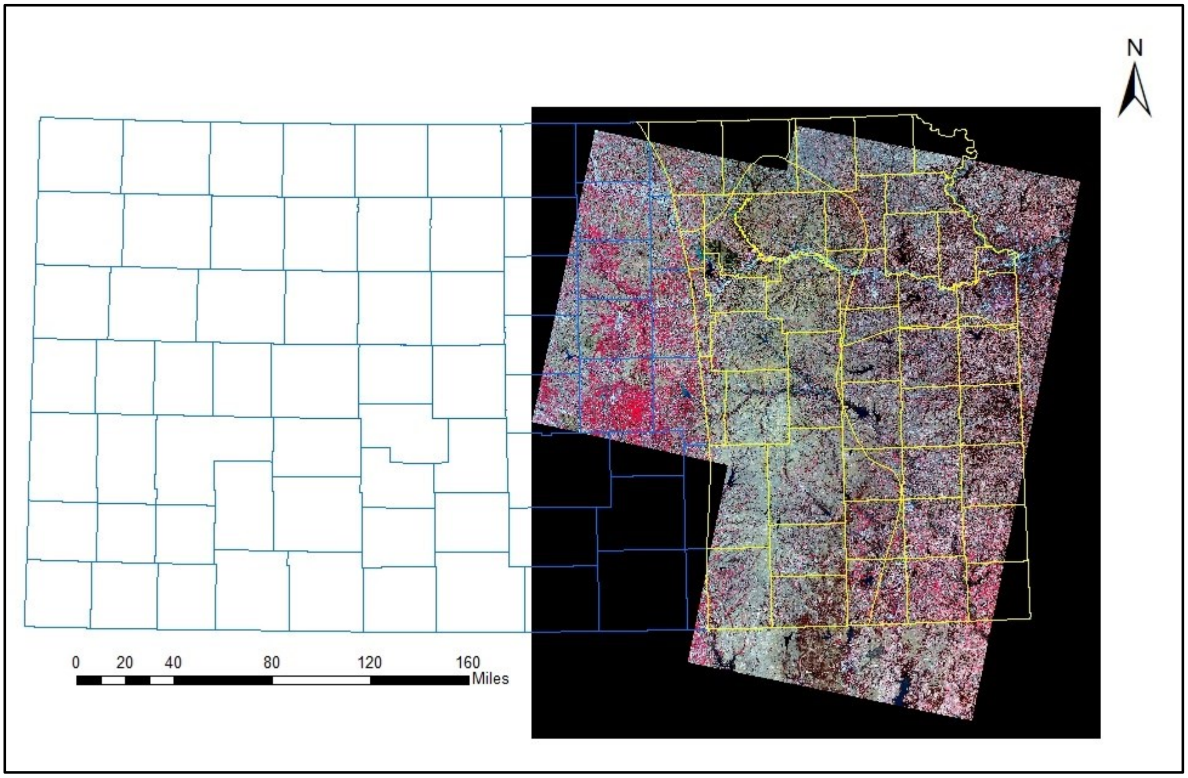


Figure 5-2. The forest-prairie ecotone of Kansas is represented by yellow county lines. Three Landsat OLI images: scene path 28/ row 33 (21st January 2017), path 27/ row 33 (03rd March 2017) and path 27/ row 34 (03rd March 2017) covers majority of the area. Images are displayed in a false color scheme: Near-infrared, red and green as RGB.

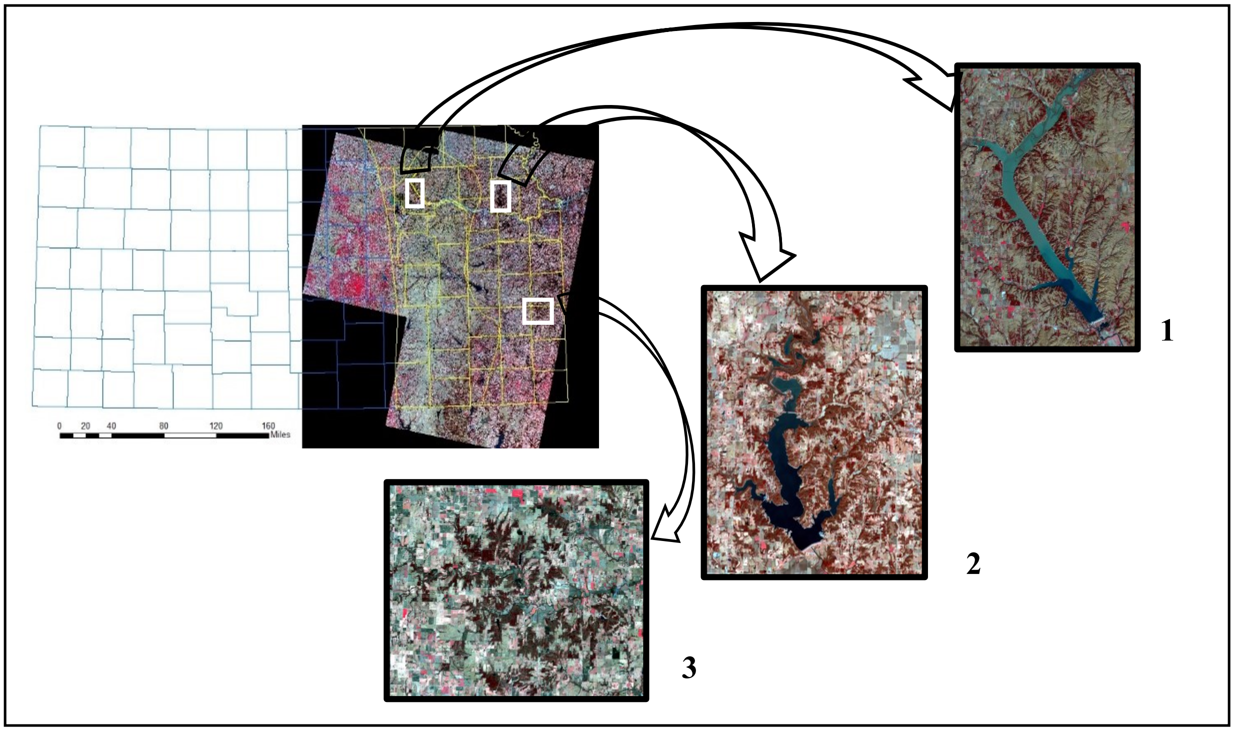


Figure 5-3. Study Areas 1). Tuttle Creek Reservoir, 2). Perry Lake, and 3). Bourbon County North

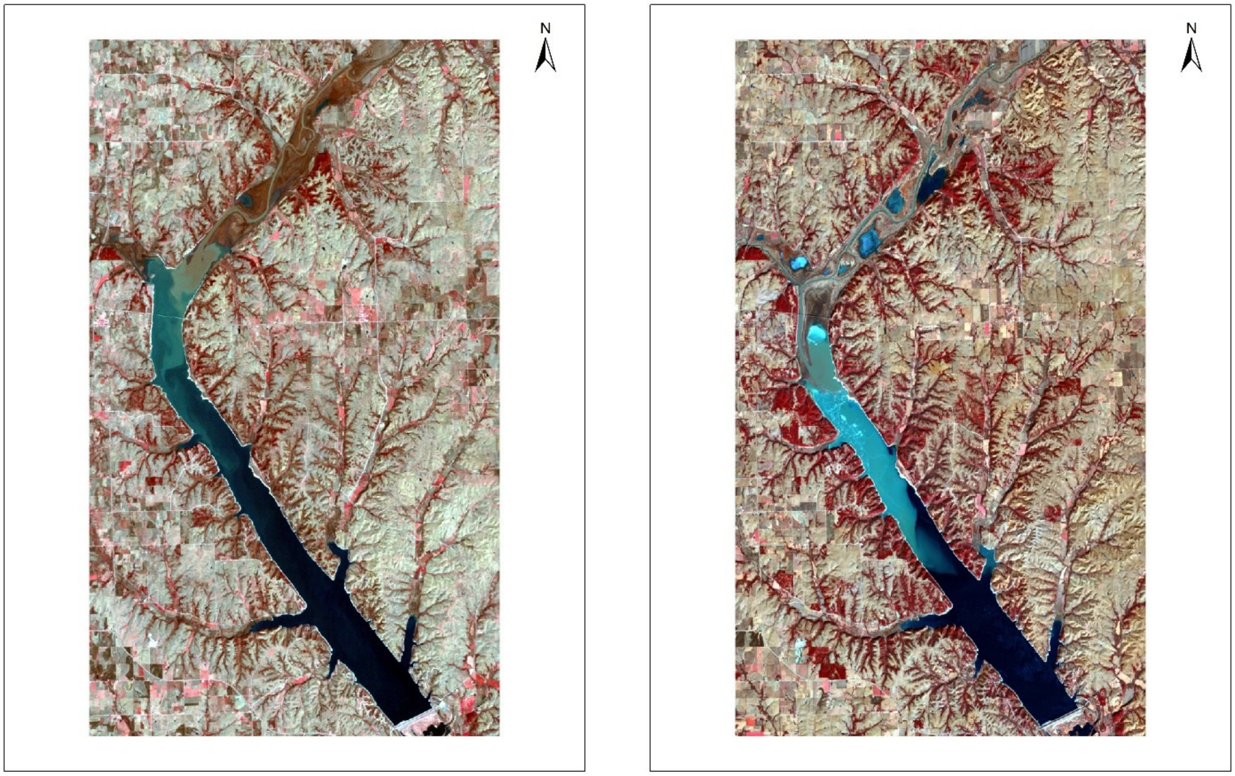


Figure 5-4. False color composite of the study region surrounding the Tuttle Creek reservoir in 1986 (left) and 2017 (right). Eastern redcedar vegetation is represented in maroon, in this dormant season image

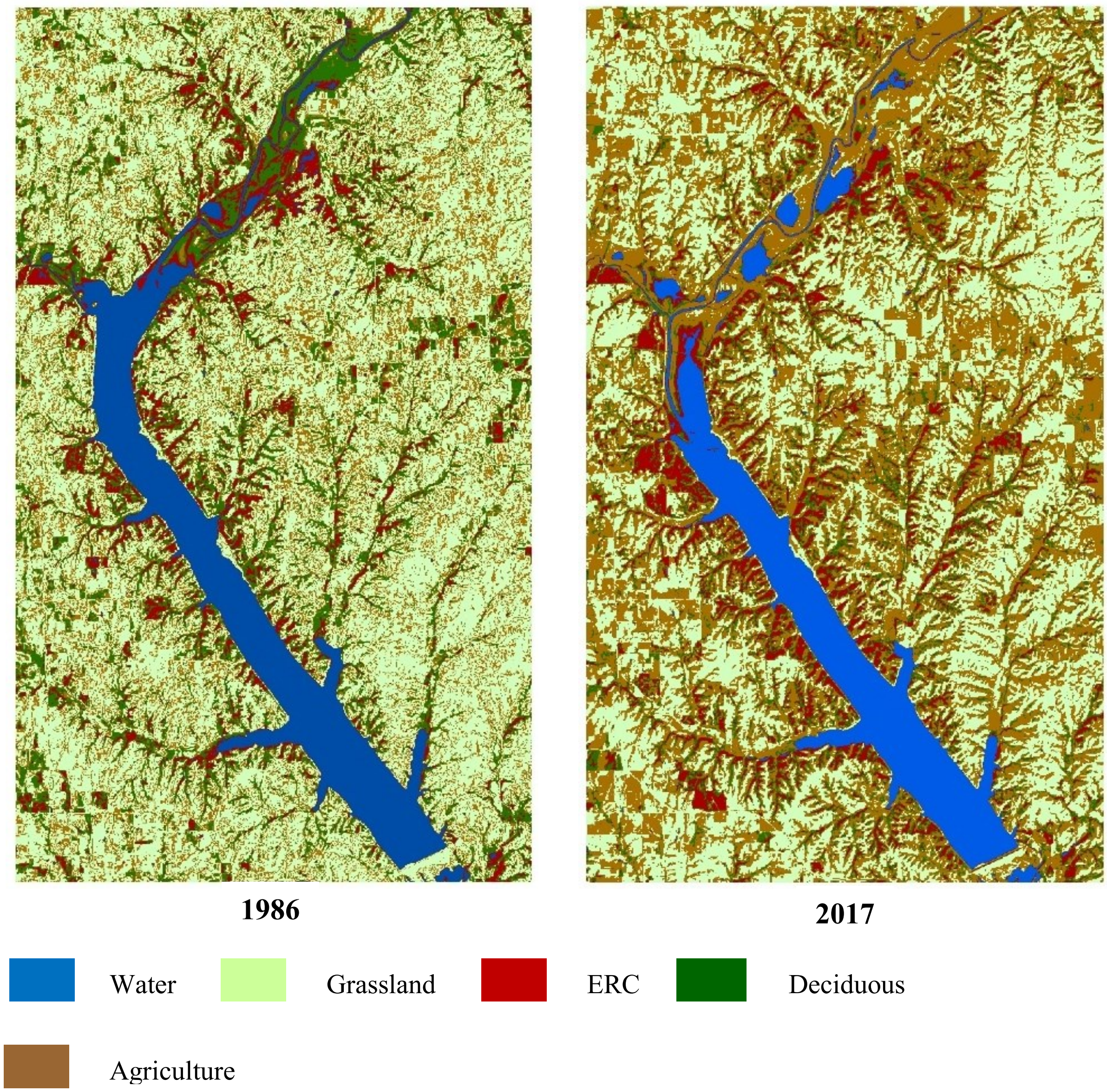


Figure 5-5. K-means clustering classification products

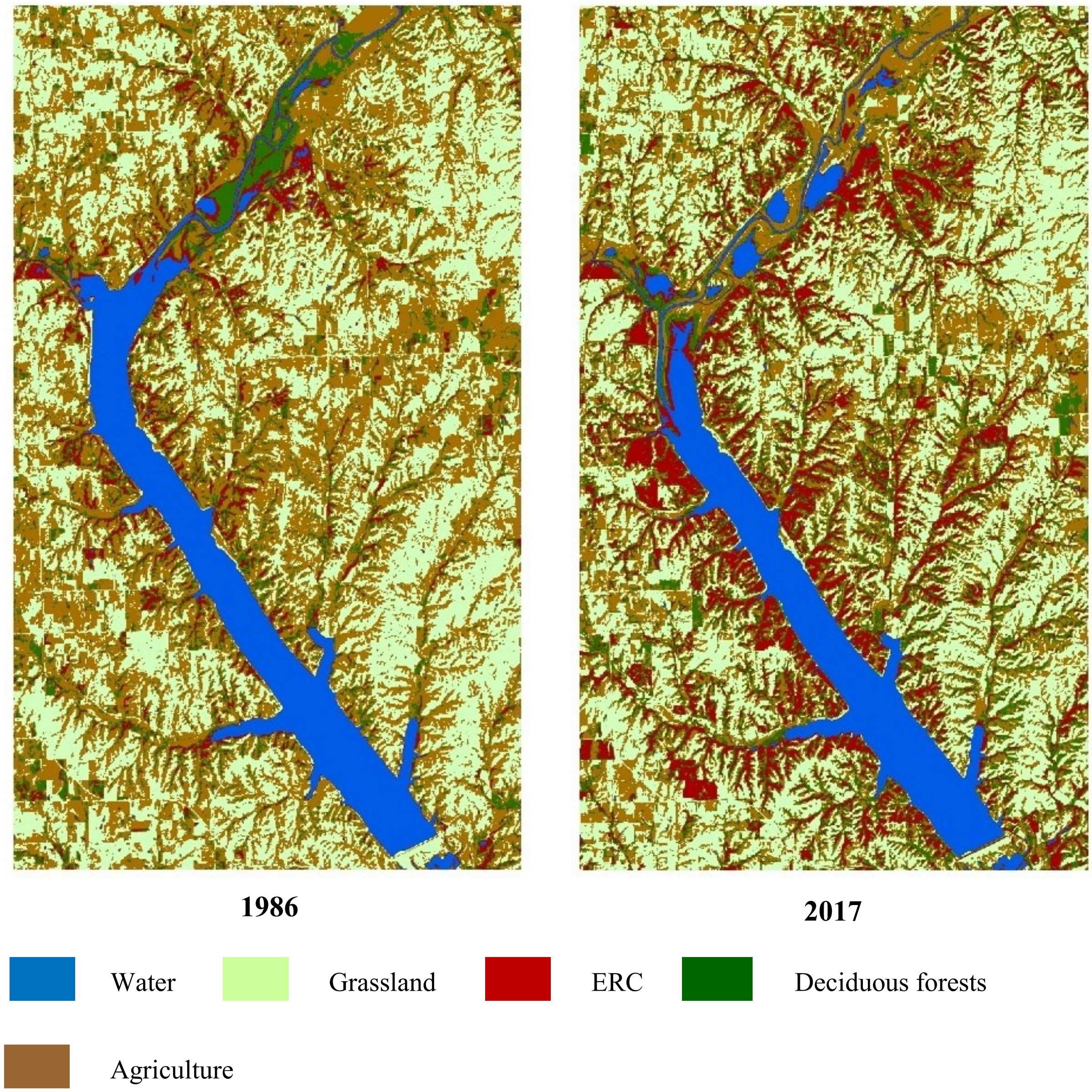


Figure 5-6. ISODATA clustering classification products

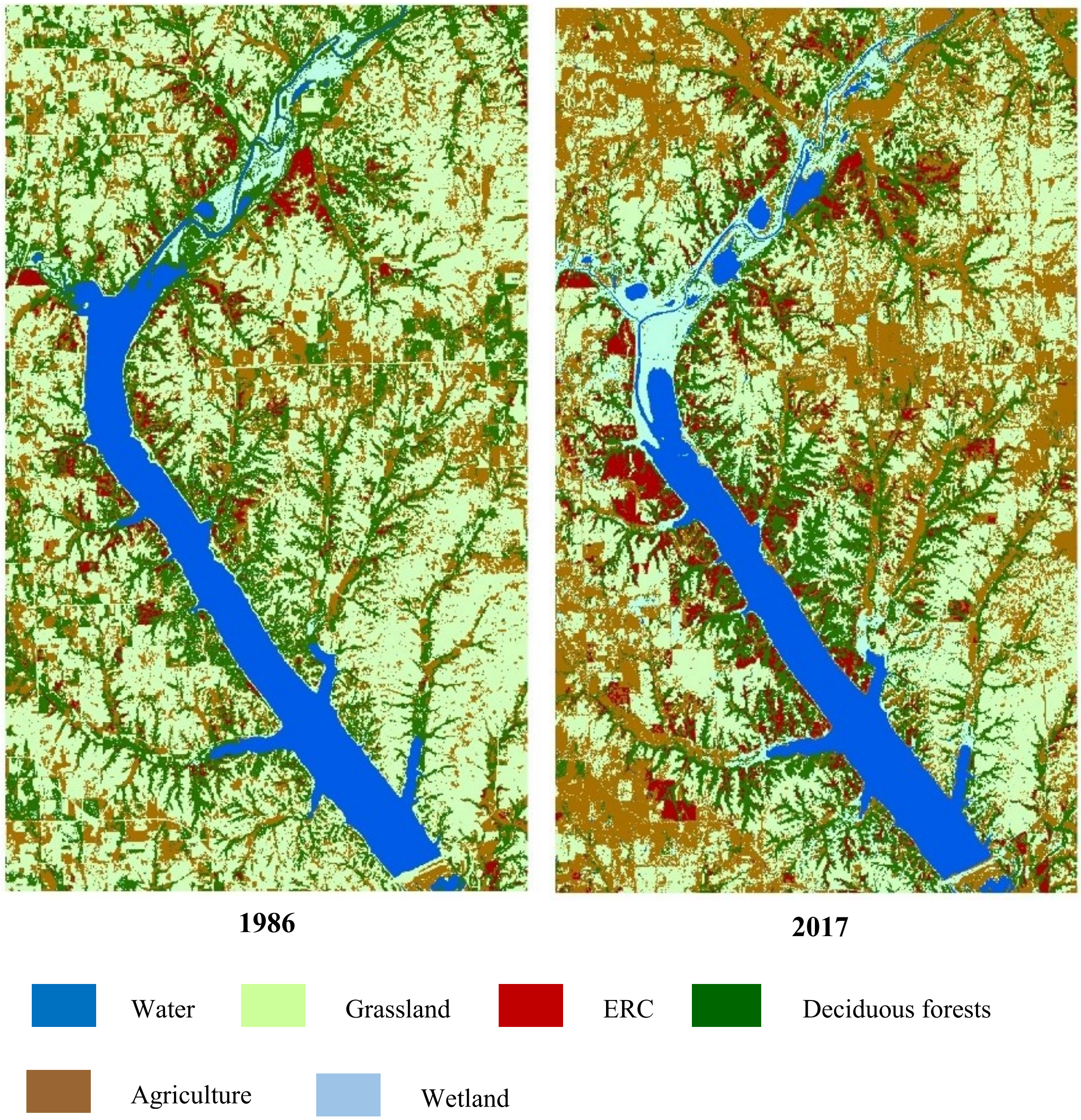


Figure 5-7. Maximum Likelihood classification products

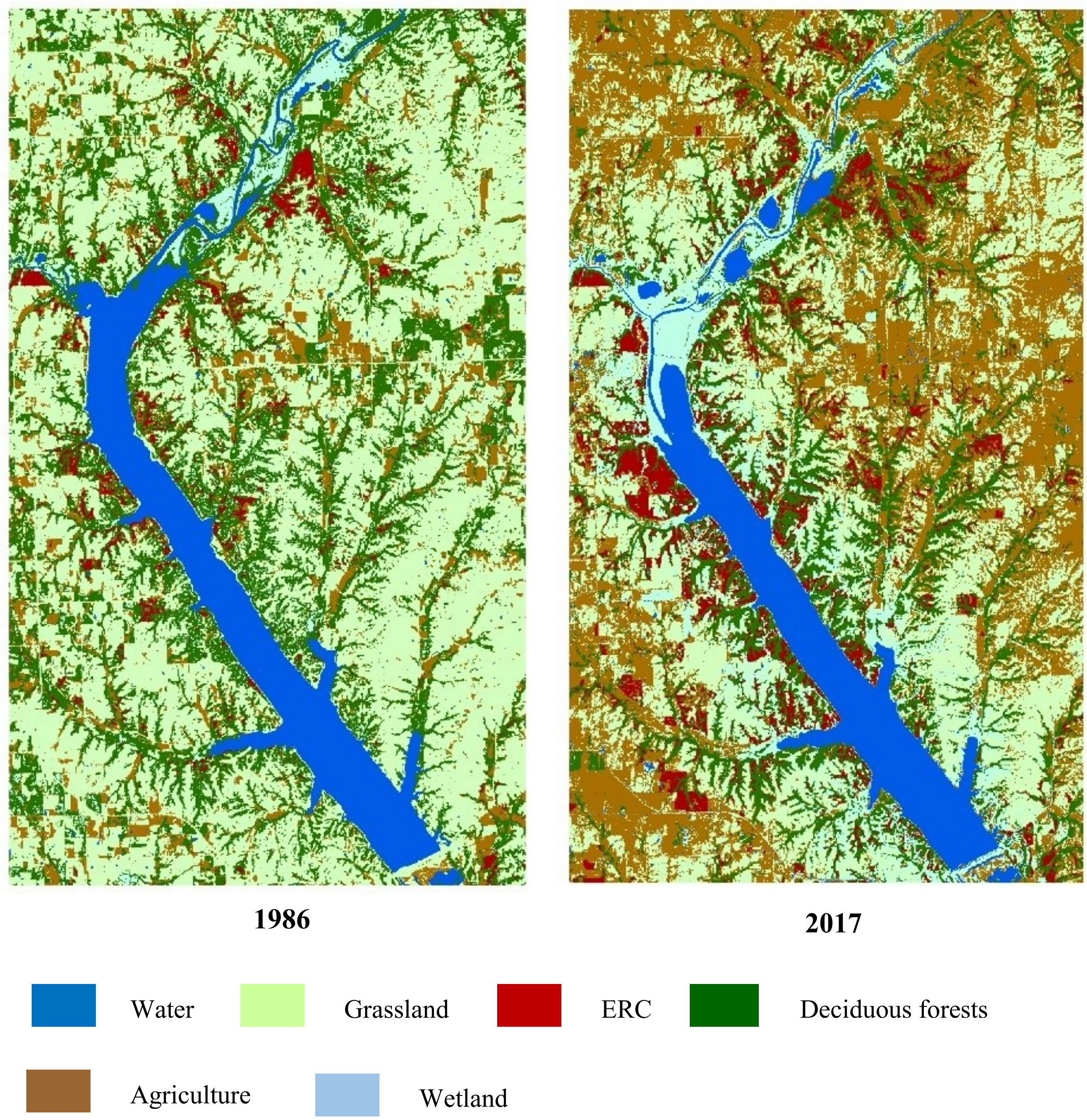


Figure 5-8. Support Vector Machine (SVM) classification products

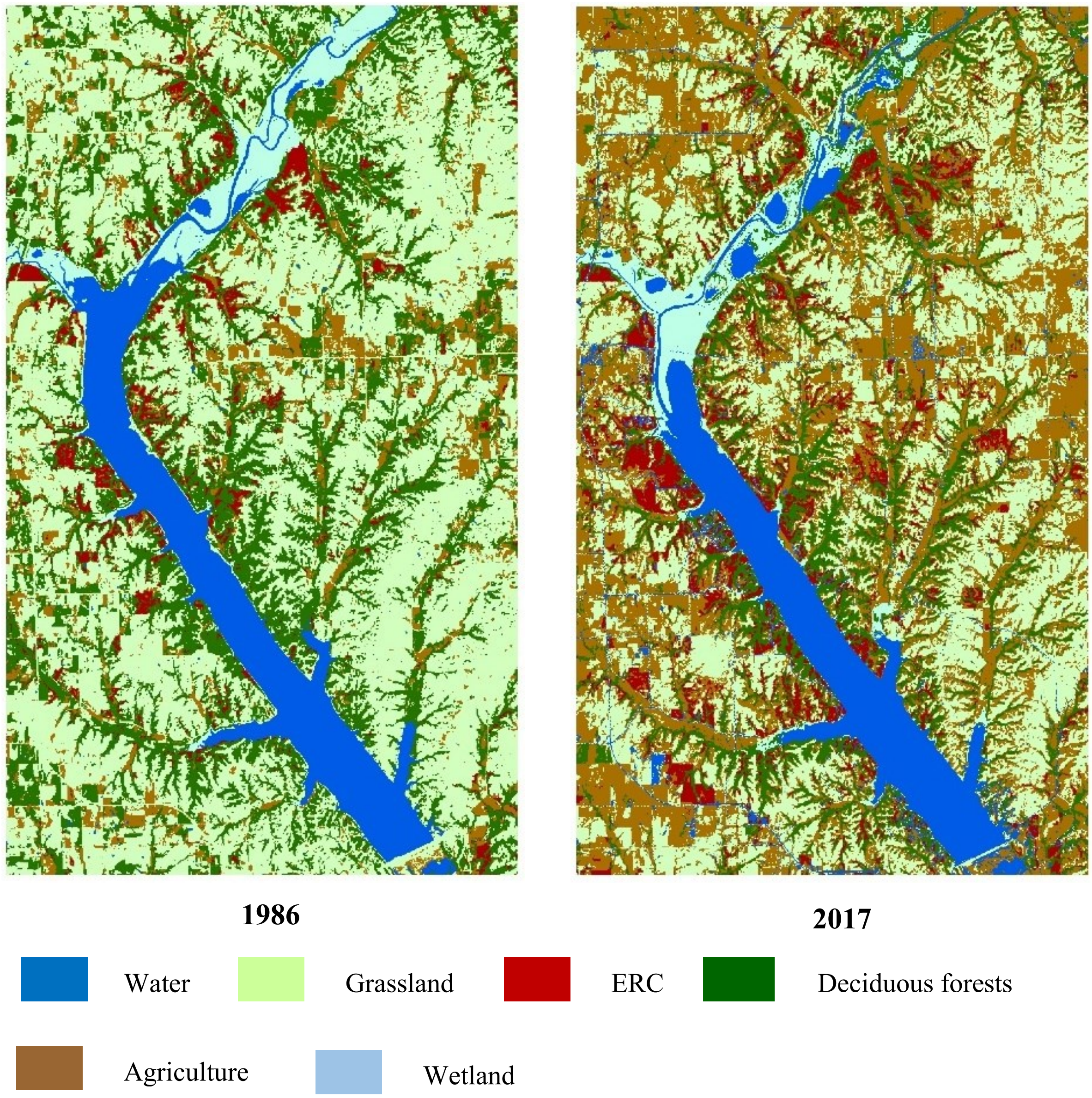


Figure 5-9. Multi-temporal SVM classification products

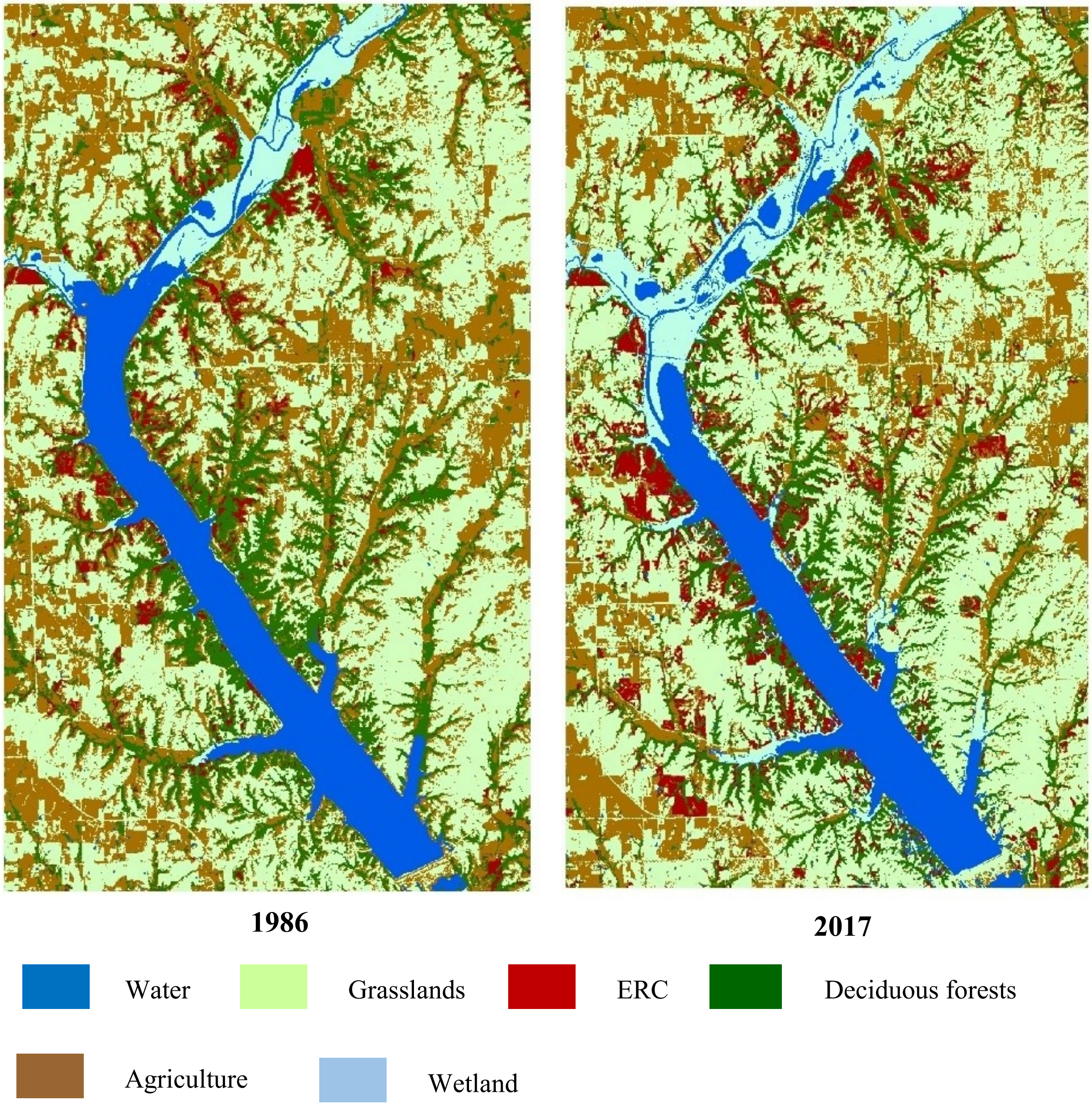


Figure 5-10. Multi-temporal SVM (improved) classification products

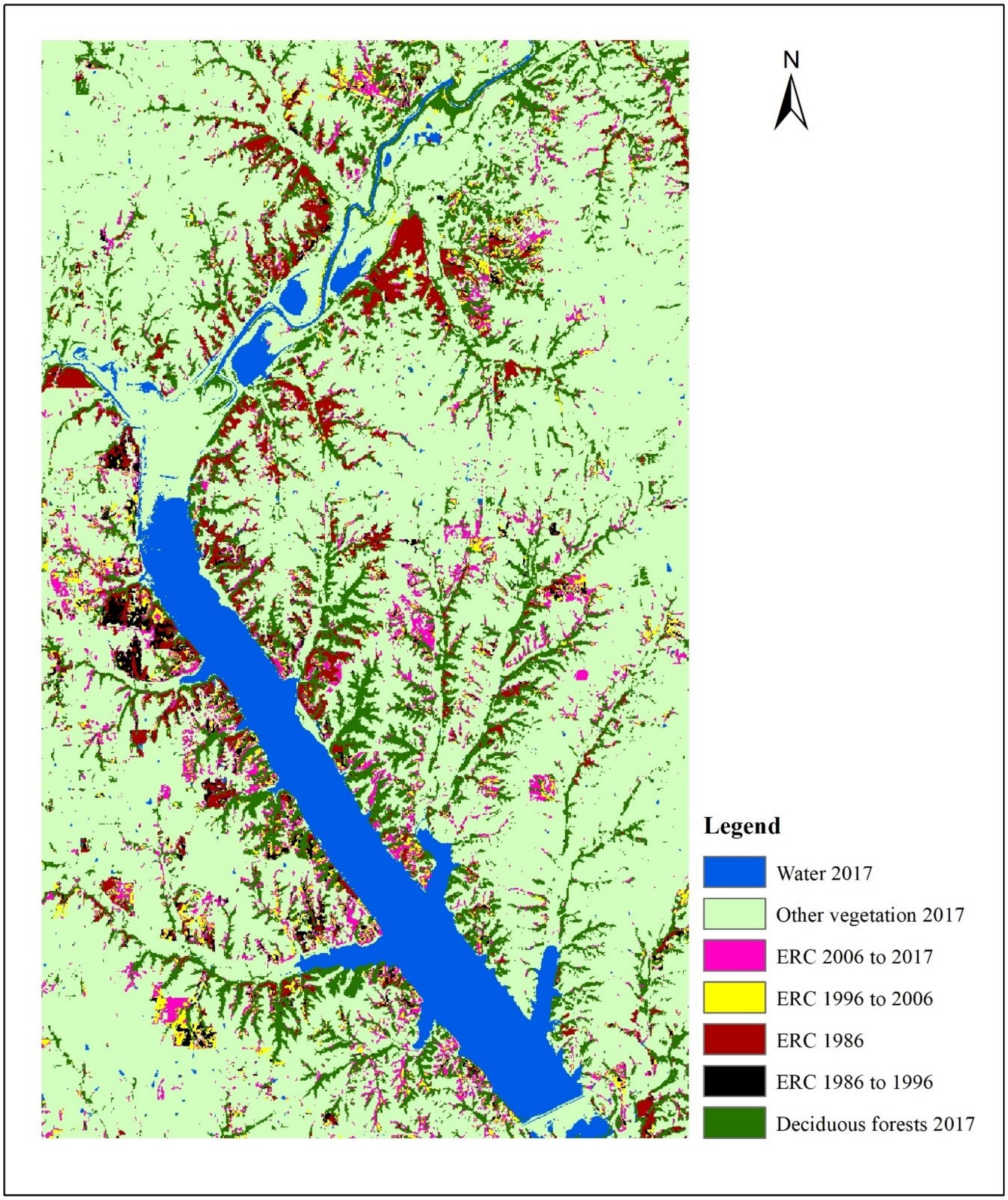


Figure 5-11. Composite image classification with SVM

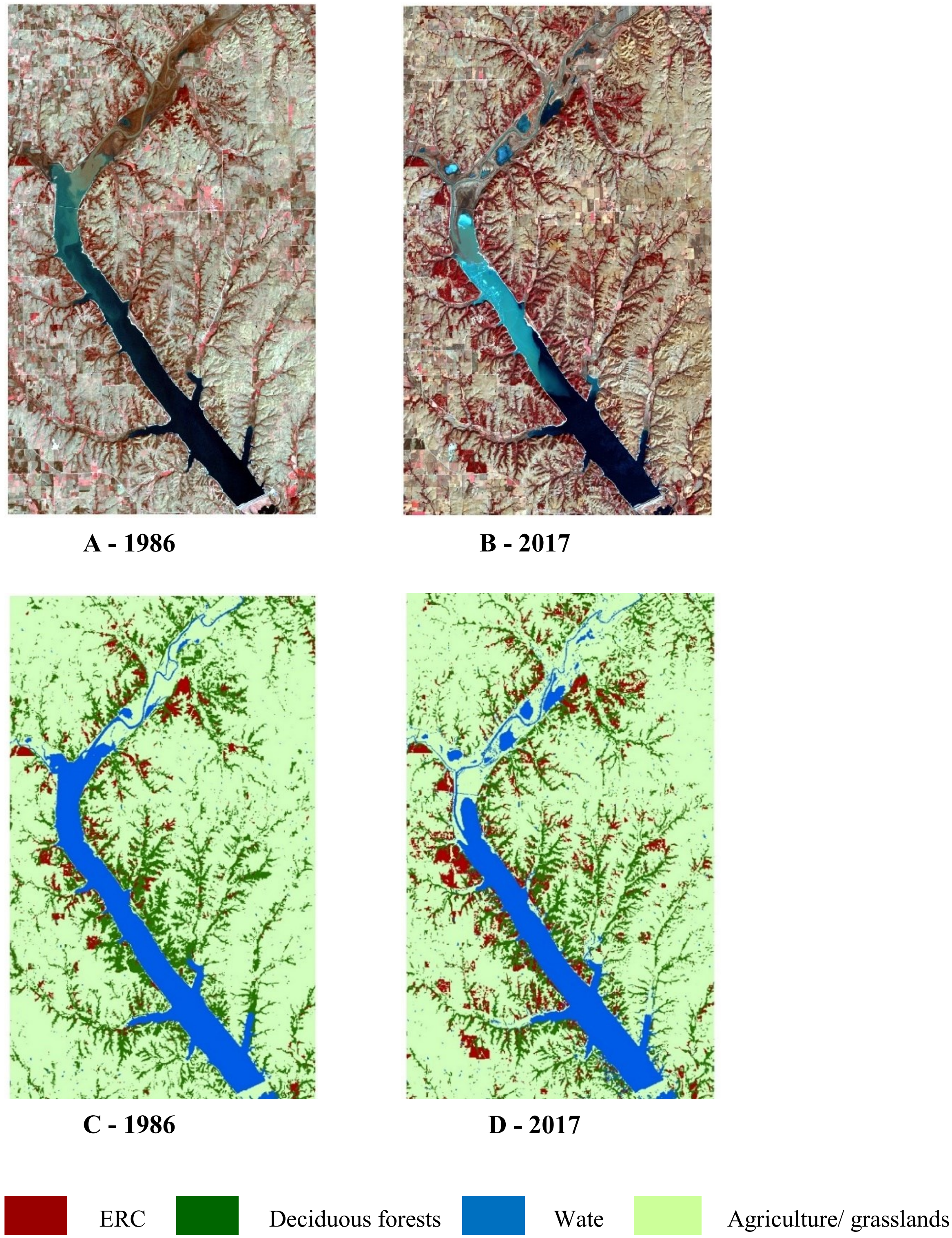


Figure 5-12. Study area 1: Tuttle Creek reservoir. A) 1986 Landsat TM image, B) 2017 Landsat OLI image, C) 1986 classified image, and D) 2017 classified image

Figure 5-13. Change map (1986 to 2017) - Tuttle Creek reservoir

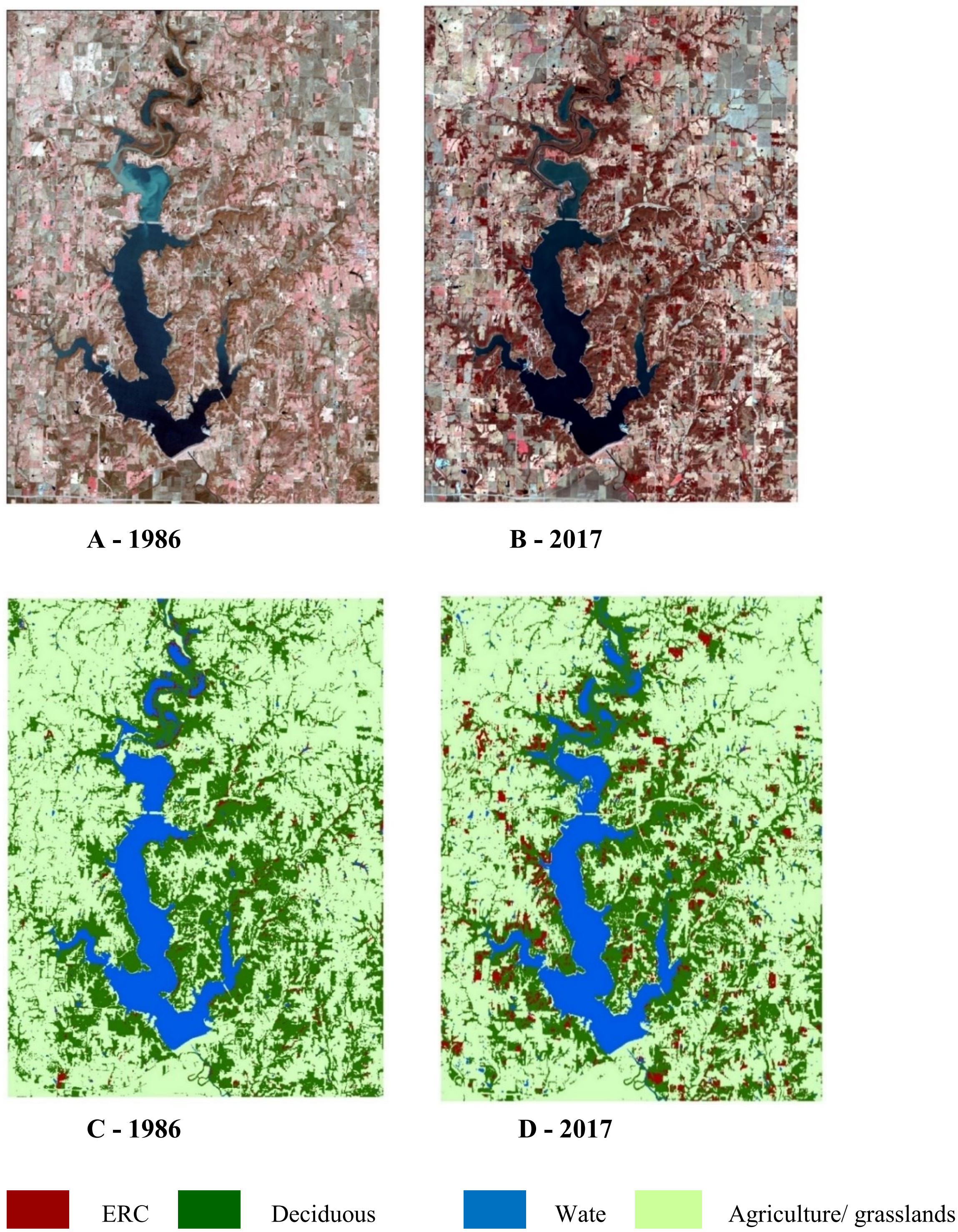


Figure 5-14. Study area 2: Perry Lake. A) 1986 Landsat TM image, B) 2017 Landsat OLI image, C) 1986 classified image, and D) 2017 classified image

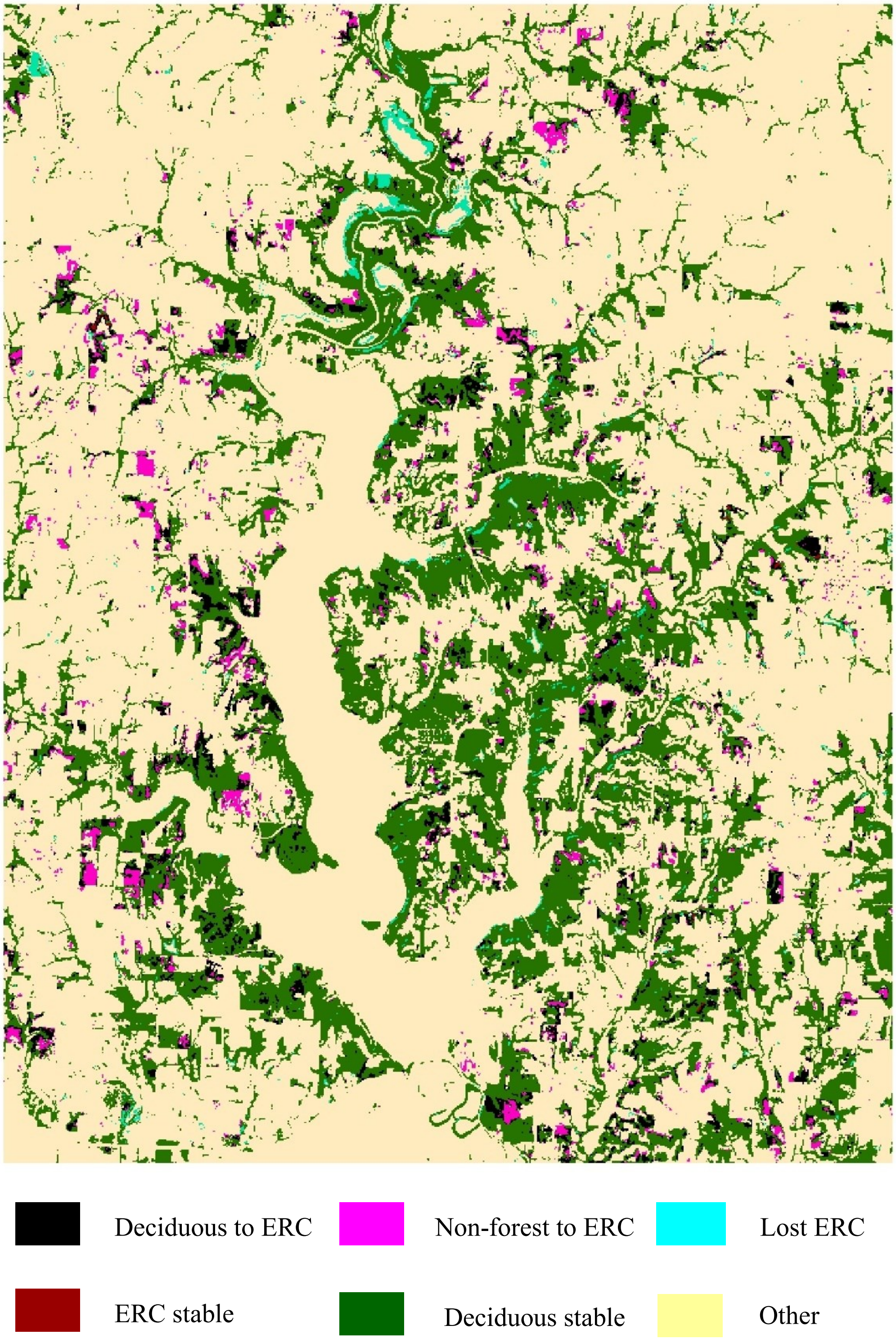


Figure 5-15. Change map (1986 to 2017) - Perry Lake

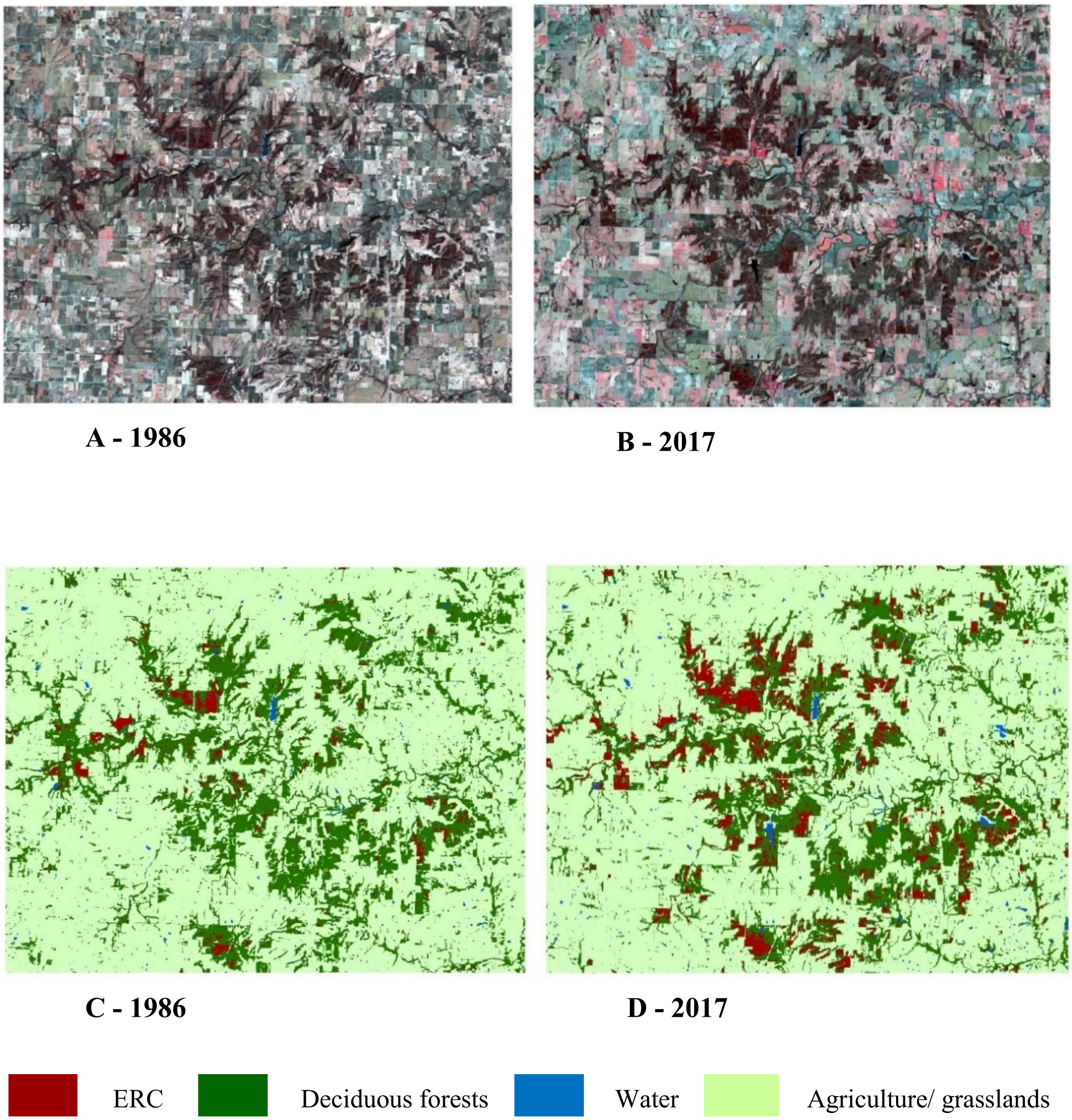


Figure 5-16. Study Area 3: Bourbon County North. A) 1986 Landsat TM image, B) 2017 Landsat OLI image, C) 1986 classified image, and D) 2017 classified image

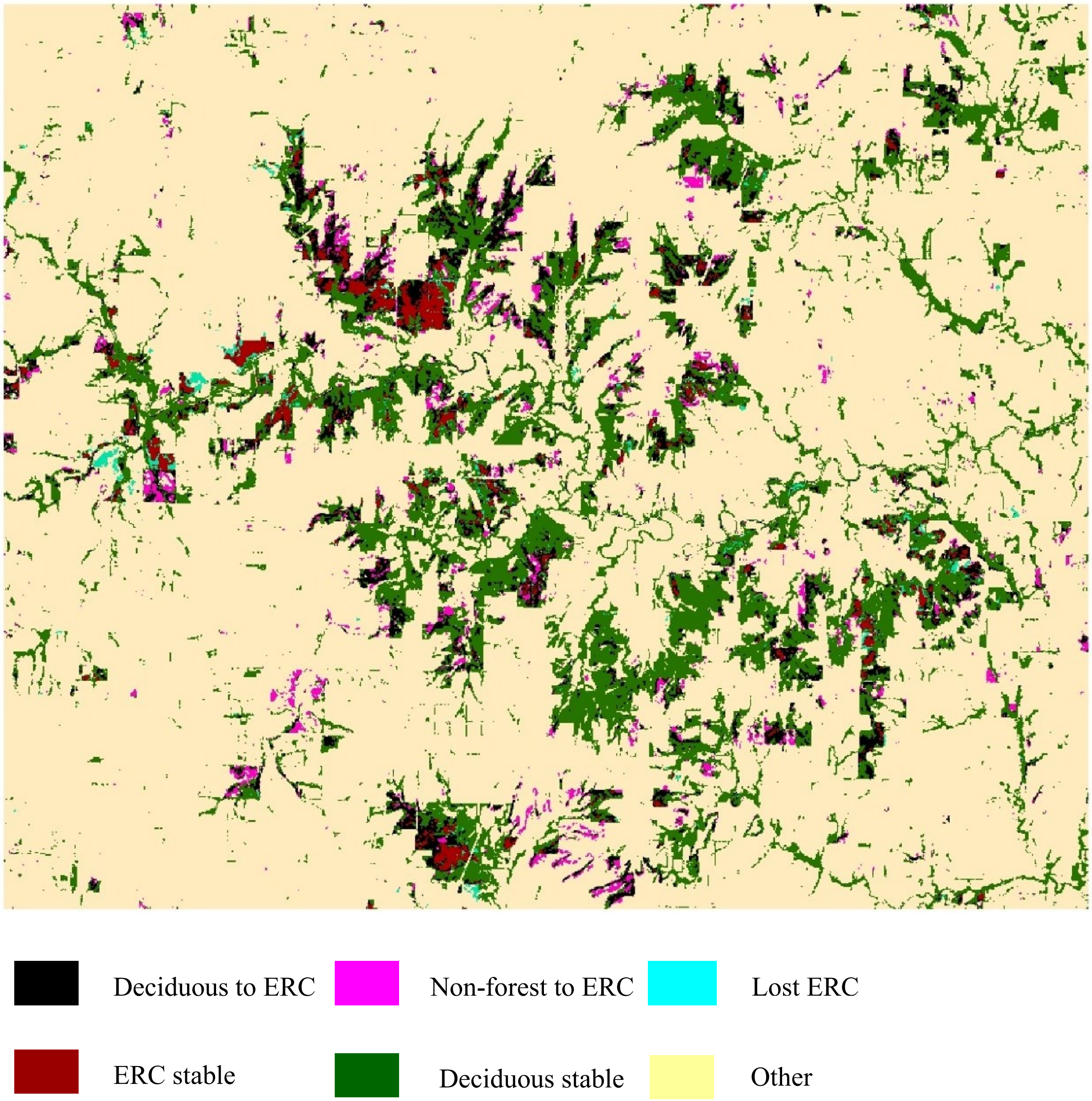


Figure 5-17. Change map (1986 to 2017) – Bourbon County north

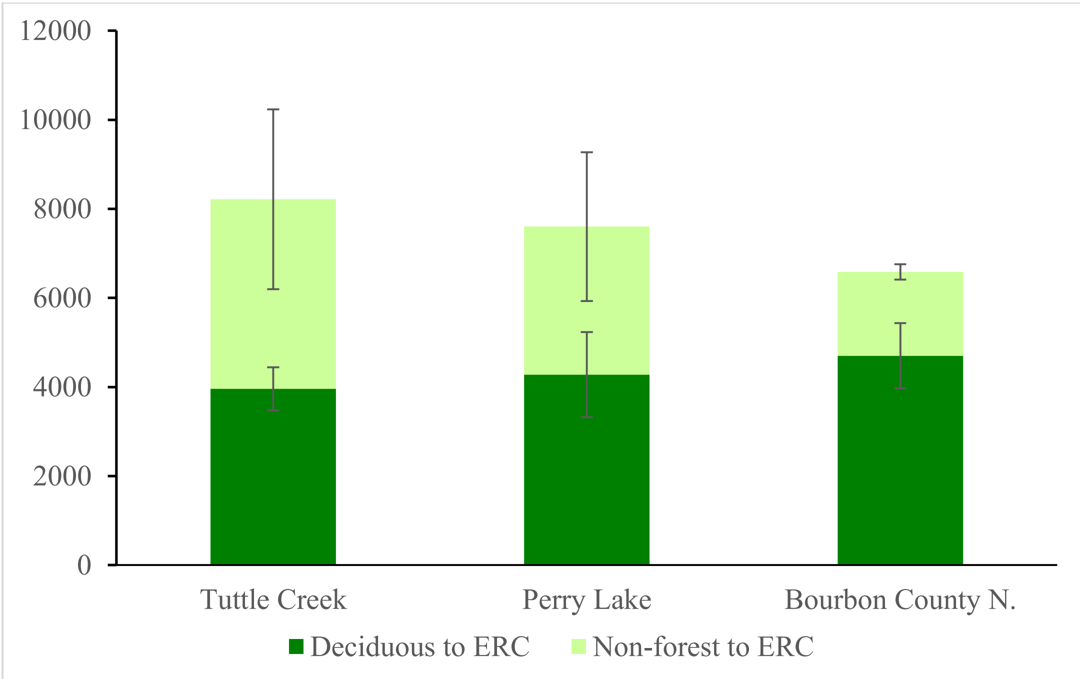


Figure 5-18. Total ERC encroachment between 1986 to 2017 for three study areas, broken by conversion of deciduous forests and non-forest classes to ERC

Table 5-1. Landsat scenes used in the study

	Season	Landsat image scenes		
		Tuttle Creek Reservoir Path 28/ row 33	Perry Lake Path 27/ row 33	Bourbon County North Path 27/ row 34
1986 - 1988	Dormant season	21st March 1986	14th March 1986	09th January 1986
	Growing season	13th September 1986	26th August 1988	07th June 1988
2015 - 2017	Dormant season	21st January 2017	03rd March 2017	03rd March 2017
	Growing season	09th June 2015	06th September 2015	22nd July 2016

Table 5-2. Class Score value assigned to each classified image

Class	1986	2017
ERC	0	0
Deciduous	1	4
Water	2	8
Agric/grassland	4	12

Table 5-3. Reclassification of change map

Change class value	Change	Reclassified class
-3	Agric/grasslands to ERC	2 - Non-forest to ERC
-2	Water to ERC	2 - Non-forest to ERC
-1	Deciduous to ERC	1 – Deciduous to ERC
0	ERC unchanged	4 – ERC stable
1	Agric/grassland to Deciduous	6 - Other
2	Water to Deciduous	6 - Other
3	Deciduous unchanged	5 – Deciduous stable
4	ERC to Deciduous	3 – ERC lost
5	Agric/grassland to water	6 - Other
6	Water unchanged	6 - Other
7	Deciduous water	6 - Other
8	ERC to water	3 – ERC lost
9	Agric/grasslands stable	6 - Other
10	Water to agric/grasslands	6 - Other
11	Deciduous to agric/grasslands	6 - Other
12	ERC to agric/grasslands	3 – ERC lost

Table 5-4. Error matrix - K-means clustering algorithm

K-means clustering - 1986

		Reference Data							
		Agric.	Grass.	Dec. woodland	ERC	Water	Wetlands	**Total**	**Users accuracy**
Classification Data	Agriculture	23	24	7	0	0	6	60	38.3
	Grassland	26	51	1	0	0	0	78	65.4
	Deciduous woodlands	18	0	31	1	0	41	91	34.1
	ERC	8	0	36	70	12	26	152	46.1
	Water	0	0	0	4	63	2	69	91.3
	Wetlands	0	0	0	0	0	0	0	-
	Total	75	75	75	75	75	75	450	
	Producers accuracy	30.7	68	41.3	93.3	84	0		
	Overall accuracy				0.53				
	Misclassification rate				0.47				
	Kappa Coefficient				0.43				

K-means clustering - 2017

		Reference Data							
		Agric.	Grass.	Dec. woodland	ERC	Water	Wetlands	**Total**	**Users accuracy**
Classification Data	Agriculture	41	20	3	0	1	41	106	38.7
	Grassland	34	54	0	0	0	1	89	60.7
	Deciduous woodlands	0	1	12	1	1	10	25	48.0
	ERC	0	0	57	74	1	19	151	49.0
	Water	0	0	3	0	72	4	79	91.1
	Wetlands	0	0	0	0	0	0	0	-
	Total	75	75	75	75	75	75	450	
	Producers accuracy	54.7	72	16	98.7	96	0		
	Overall accuracy				0.56				
	Misclassification rate				0.44				
	Kappa Coefficient				0.47				

Table 5-5. Error matrix - ISODATA classification

ISODATA - 1986

		Reference Data							
		Agric.	Grass.	Dec. woodland	ERC	Water	Wetlands	**Total**	**Users accuracy**
Classification Data	Agriculture	29	17	22	0	0	15	83	34.9
	Grassland	27	58	0	0	0	0	85	68.2
	Deciduous woodlands	15	0	25	2	1	47	90	27.8
	ERC	4	0	28	69	9	11	121	57.0
	Water	0	0	0	4	65	2	71	91.5
	Wetlands	0	0	0	0	0	0	0	-
	Total	75	75	75	75	75	75	450	
	Producers accuracy	38.7	77.3	33.3	92	86.7	0		
	Overall accuracy				0.55				
	Misclassification rate				0.45				
	Kappa Coefficient				0.46				

ISODATA - 2017

		Reference Data							
		Agric.	Grass.	Dec. woodland	ERC	Water	Wetlands	**Total**	**Users accuracy**
Classification Data	Agriculture	23	21	1	0	0	26	**71**	32.4
	Grassland	52	53	0	0	0	1	**106**	50.0
	Deciduous woodlands	0	0	4	0	1	18	**23**	17.4
	ERC	0	1	66	75	2	17	**161**	46.6
	Water	0	0	4	0	72	13	**89**	80.9
	Wetlands	0	0	0	0	0	0	**0**	-
	Total	**75**	**75**	**75**	**75**	**75**	**75**	**450**	
	Producers accuracy	30.7	70.7	5.3	100	96	0		
	Overall accuracy				0.50				
	Misclassification rate				0.50				
	Kappa Coefficient				0.41				

Table 5-6. Error matrix - Maximum likelihood classification

Maximum Likelihood - 1986

		Reference Data							
		Agric.	Grass.	Dec. woodland	ERC	Water	Wetlands	**Total**	**Users accuracy**
Classification Data	Agriculture	54	2	0	0	8	0	64	84.4
	Grassland	3	73	0	0	2	0	78	93.6
	Deciduous woodlands	15	0	66	1	8	19	109	60.6
	ERC	1	0	0	74	0	0	75	98.7
	Water	0	0	0	0	57	1	58	98.3
	Wetlands	2	0	9	0	0	55	66	83.3
	Total	75	75	75	75	75	75	450	
	Producers accuracy	72	97.3	88	98.7	76	73.3		
	Overall accuracy			0.84					
	Misclassification rate			0.16					
	Kappa Coefficient			0.81					

Maximum Likelihood - 2017

		Reference Data							
		Agric.	Grass.	Dec. woodland	ERC	Water	Wetlands	**Total**	**Users accuracy**
Classification Data	Agriculture	68	12	0	0	0	8	88	77.3
	Grassland	1	63	0	0	0	0	64	98.4
	Deciduous woodlands	0	0	75	3	0	10	88	85.2
	ERC	5	0	0	72	0	0	77	93.5
	Water	0	0	0	0	74	0	74	100.0
	Wetlands	1	0	0	0	1	57	59	96.6
	Total	75	75	75	75	75	75	450	
	Producers accuracy	90.7	84	100	96	98.7	76		
	Overall accuracy			0.91					
	Misclassification rate			0.09					
	Kappa Coefficient			0.89					

Table 5-7. Error matrix -Support Vector Machines (SVM)

Support Vector Machines - 1986

		Reference Data							
		Agric.	Grass.	Dec. woodland	ERC	Water	Wetlands	**Total**	**Users accuracy**
Classification Data	Agriculture	54	0	0	0	0	0	54	100.0
	Grassland	2	75	0	0	0	0	77	97.4
	Deciduous woodlands	15	0	60	1	0	14	90	66.7
	ERC	1	0	1	74	0	0	76	97.4
	Water	0	0	0	0	75	2	77	97.4
	Wetlands	3	0	14	0	0	59	76	77.6
	Total	75	75	75	75	75	75	450	
	Producers accuracy	72	100	80	98.7	100	78.7		
	Overall accuracy			0.88					
	Misclassification rate			0.12					
	Kappa Coefficient			0.86					

Support Vector Machines - 2017

		Reference Data							
		Agric.	Grass.	Dec. woodland	ERC	Water	Wetlands	**Total**	**Users accuracy**
Classification Data	Agriculture	59	11	0	0	0	4	74	79.7
	Grassland	4	63	0	0	0	2	69	91.3
	Deciduous woodlands	0	1	74	5	0	14	94	78.7
	ERC	12	0	0	70	0	3	85	82.4
	Water	0	0	0	0	75	0	75	100.0
	Wetlands	0	0	1	0	0	52	53	98.1
	Total	75	75	75	75	75	75	450	
	Producers accuracy	78.7	84	98.7	93.3	100	69.3		
	Overall accuracy			0.87					
	Misclassification rate			0.12					
	Kappa Coefficient			0.85					

Table 5-8. Error matrix - Multi-seasonal SVM classification

Multi-seasonal SVM - 1986

		Reference Data							
		Agric.	Grass.	Dec. woodland	ERC	Water	Wetlands	**Total**	**Users accuracy**
Classification Data	Agriculture	54	0	0	0	0	0	54	100.0
	Grassland	2	74	0	0	0	0	76	97.4
	Deciduous woodlands	19	1	74	1	0	7	102	72.5
	ERC	0	0	1	74	0	0	75	98.7
	Water	0	0	0	0	75	3	78	96.2
	Wetlands	0	0	0	0	0	65	65	100.0
	Total	75	75	75	75	75	75	450	
	Producers accuracy	72	98.7	98.7	98.7	100	86.7		
	Overall accuracy				0.92				
	Misclassification rate				0.08				
	Kappa Coefficient				0.91				

Multi-seasonal SVM - 2017

		Reference Data							
		Agric.	Grass.	Dec. woodland	ERC	Water	Wetlands	**Total**	**Users accuracy**
Classification Data	Agriculture	57	9	0	0	1	1	68	83.8
	Grassland	2	65	0	0	0	1	68	95.6
	Deciduous woodlands	0	1	75	5	0	16	97	77.3
	ERC	15	0	0	70	0	0	85	82.4
	Water	1	0	0	0	74	2	77	96.1
	Wetlands	0	0	0	0	0	55	55	100.0
	Total	75	75	75	75	75	75	450	
	Producers accuracy	76	86.7	100	93.3	98.7	73.3		
	Overall accuracy				0.88				
	Misclassification rate				0.12				
	Kappa Coefficient				0.86				

Table 5-9. Error matrix - Multi-seasonal SVM (improved)

Multi-seasonal SVM (improved) - 1986

	Reference Data							
	Agric.	Grass.	Dec. woodland	ERC	Water	Wetlands	**Total**	**Users accuracy**
Agriculture	75	9	6	0	1	0	91	82.4
Grassland	0	66	0	0	0	0	66	100.0
Deciduous woodlands	0	0	68	1	0	8	77	88.3
ERC	0	0	1	74	0	0	75	98.7
Water	0	0	0	0	74	3	77	96.1
Wetlands	0	0	0	0	0	64	64	100.0
Total	75	75	75	75	75	75	450	83.3
Producers accuracy	100	88	90.7	98.7	98.7	85.3		
Overall accuracy			0.94					
Misclassification rate			0.06					
Kappa Coefficient			0.93					

Multi-seasonal SVM (improved) - 2017

	Reference Data							
	Agric.	Grass.	Dec. woodland	ERC	Water	Wetlands	**Total**	**Users accuracy**
Agriculture	70	0	2	0	0	1	73	95.9
Grassland	2	74	0	0	0	1	77	96.1
Deciduous woodlands	0	1	72	4	0	0	77	93.5
ERC	0	0	1	71	0	0	72	98.6
Water	0	0	0	0	75	4	79	94.9
Wetlands	3	0	0	0	0	69	72	95.8
Total	75	75	75	75	75	75	450	
Producers accuracy	93.3	98.7	96	94.7	100	92		
Overall accuracy			0.96					
Misclassification rate			0.04					
Kappa Coefficient			0.95					

Table 5-10. Error matrix of sample counts - Tuttle Creek Reservoir Change Map

		Reference classes								
		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	**Total**	**Area (pixels)**	**W_i (proportion)**
Mapped classes	Class 1	72	0	0	3	0	0	**75**	16085	0.022
	Class 2	3	69	0	2	0	1	**75**	15493	0.021
	Class 3	0	0	60	7	5	3	**75**	8777	0.012
	Class 4	3	3	1	68	0	0	**75**	13632	0.019
	Class 5	2	0	0	0	93	5	**100**	67693	0.093
	Class 6	0	1	0	0	1	128	**131**	602497	0.832
	Total	**80**	**73**	**61**	**80**	**99**	**138**	**531**	724177	

Class 1: Deciduous to ERC, Class 2: Non-forest to ERC, Class 3: ERC lost, Class 4: ERC stable, Class 5: Deciduous forests stable, and Class 6: Other

Table 5-11. Error matrix with estimated proportions of area - Tuttle Creek reservoir

		Reference classes								
		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	**Total (Wi)**	**Area (pixels)**	**Area (acres)**
Mapped classes	Class 1	0.0211	0.0000	0.0000	0.0009	0.0000	0.0000	**0.022**	16085	3577
	Class 2	0.0008	0.0193	0.0000	0.0006	0.0000	0.0003	**0.021**	15493	3446
	Class 3	0.0000	0.0000	0.0096	0.0011	0.0008	0.0005	**0.012**	8777	1952
	Class 4	0.0008	0.0008	0.0003	0.0172	0.0000	0.0000	**0.019**	13632	3032
	Class 5	0.0019	0.0000	0.0000	0.0000	0.0865	0.0047	**0.093**	67693	15055
	Class 6	0.0000	0.0064	0.0000	0.0000	0.0127	0.8129	**0.832**	602497	133992
	Total*	**0.0246**	**0.0264**	**0.0099**	**0.0198**	**0.1000**	**0.8184**	**1.00**	**724177**	161053

Class 1: Deciduous to ERC, Class 2: Non-forest to ERC, Class 3: ERC lost, Class 4: ERC stable, Class 5: Deciduous forests stable, and Class 6: Other

***Total values represented for each column is the unbiased estimator of the total area for that class**

Table 5-12. Area estimations with 95% Confidence Intervals - Tuttle Creek reservoir

	Estimated Area proportion	**Area (acres)**	**± 95 % CI (acres)**	**Margin of Error**	**User's accuracy (± 95% CI)**	**Producer's accuracy**
Deciduous to ERC	**0.0246**	3959	487	12%	0.96 (± 0.04)	0.86
Non-forest to ERC	**0.0264**	4257	2020	47%	0.92 (± 0.06)	0.73
ERC lost	**0.0099**	1587	193	12%	0.80 (± 0.09)	0.97
ERC stable	**0.0198**	3187	313	10%	0.91 (± 0.07)	0.87
Deciduous stable	**0.1000**	16104	2925	18%	0.93 (± 0.05)	0.86
Other	**0.8184**	131799	3507	3%	0.98 (± 0.03)	0.99
Overall accuracy				**0.96 (± 0.02)**		

Table 5-13. Error matrix of sample counts - Perry lake change map

		Reference classes								
		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	**Total**	**Area (pixels)**	**W_i (proportion)**
Mapped classes	Class 1	68	3	0	0	4	0	**75**	17932	0.027
	Class 2	0	71	0	0	1	3	**75**	11014	0.017
	Class 3	0	0	65	1	0	9	**75**	4146	0.006
	Class 4	0	0	1	66	4	4	**75**	277	0.000
	Class 5	2	0	1	0	92	5	**100**	149618	0.228
	Class 6	0	1	0	0	2	122	**125**	474473	0.722
	Total	**70**	**75**	**67**	**67**	**103**	**143**	**525**	657460	

Class 1: Deciduous to ERC, Class 2: Non-forest to ERC, Class 3: ERC lost, Class 4: ERC stable, Class 5: Deciduous forests stable, and Class 6: Other

Table 5-14. Error matrix with estimated proportions of area – Perry lake

Mapped classes	Reference classes: Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Total (Wi)	Area (pixels)	Area (acres)
Class 1	0.0247	0.0011	0.0000	0.0000	0.0015	0.0000	**0.027**	17932	3988
Class 2	0.0000	0.0159	0.0000	0.0000	0.0002	0.0007	**0.017**	11014	2449
Class 3	0.0000	0.0000	0.0055	0.0001	0.0000	0.0008	**0.006**	4146	922
Class 4	0.0000	0.0000	0.0000	0.0004	0.0000	0.0000	**0.000**	277	62
Class 5	0.0046	0.0000	0.0023	0.0000	0.2094	0.0114	**0.228**	149618	33274
Class 6	0.0000	0.0058	0.0000	0.0000	0.0115	0.7044	**0.722**	474473	105520
Total*	**0.0293**	**0.0227**	**0.0077**	**0.0005**	**0.2226**	**0.7172**	**1.00**	**657460**	146215

Class 1: Deciduous to ERC, Class 2: Non-forest to ERC, Class 3: ERC lost, Class 4: ERC stable, Class 5: Deciduous forests stable, and Class 6: Other

***Total values represented for each column is the unbiased estimator of the total area for that class**

Table 5-15. Area estimations with 95% Confidence Intervals - Perry lake

	Estimated Area proportion	**Area (acres)**	**± 95 % CI (acres)**	**Margin of Error**	**User's accuracy (± 95% CI)**	**Producer's accuracy**
Deciduous to ERC	**0.0293**	4281	955	22%	0.91 (± 0.07)	0.84
Non-forest to ERC	**0.0227**	3322	1669	50%	0.95 (± 0.05)	0.70
ERC lost	**0.0077**	1133	656	58%	0.87 (± 0.08)	0.71
ERC stable	**0.0005**	67	25	37%	0.88 (± 0.07)	0.82
Deciduous stable	**0.2226**	32549	2939	9%	0.92 (± 0.05)	0.94
Other	**0.7172**	104863	3184	3%	0.98 (± 0.03)	0.98
Overall accuracy				**0.96 (± 0.02)**		

Table 5-16. Error matrix of sample counts – Bourbon County North change map

		Reference classes								
		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	**Total**	**Area (pixels)**	**W_i (proportion)**
Mapped classes	Class 1	61	0	0	0	11	3	**75**	22777	0.033
	Class 2	0	65	0	0	2	8	**75**	9664	0.014
	Class 3	3	0	61	2	2	7	**75**	2718	0.004
	Class 4	6	1	1	67	0	0	**75**	8114	0.012
	Class 5	2	0	0	0	95	3	**100**	92607	0.135
	Class 6	0	0	0	0	6	122	**128**	551755	0.802
	Total	**72**	**66**	**62**	**69**	**116**	**143**	**528**	687635	

Class 1: Deciduous to ERC, Class 2: Non-forest to ERC, Class 3: ERC lost, Class 4: ERC stable, Class 5: Deciduous forests stable, and Class 6: Other

Table 5-17. Error matrix with estimated proportions of area – Bourbon County North

		Reference classes								
		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	**Total (Wi)**	**Area (pixels)**	**Area (acres)**
Mapped classes	Class 1	0.0269	0.0000	0.0000	0.0000	0.0049	0.0013	**0.033**	22777	5065
	Class 2	0.0000	0.0122	0.0000	0.0000	0.0004	0.0015	**0.014**	9664	2149
	Class 3	0.0002	0.0000	0.0032	0.0001	0.0001	0.0004	**0.004**	2718	604
	Class 4	0.0009	0.0002	0.0002	0.0105	0.0000	0.0000	**0.012**	8114	1805
	Class 5	0.0027	0.0000	0.0000	0.0000	0.1279	0.0040	**0.135**	92607	20595
	Class 6	0.0000	0.0000	0.0000	0.0000	0.0376	0.7648	**0.802**	551755	122707
	Total*	**0.0307**	**0.0123**	**0.0034**	**0.0106**	**0.1709**	**0.7720**	**1.00**	687635	152926

Class 1: Deciduous to ERC, Class 2: Non-forest to ERC, Class 3: ERC lost, Class 4: ERC stable, Class 5: Deciduous forests stable, and Class 6: Other

***Total values represented for each column is the unbiased estimator of the total area for that class**

Table 5-18. Area estimations with 95% Confidence Intervals - Bourbon County North

	Estimated Area proportion	**Area (acres)**	**± 95 % CI (acres)**	**Margin of Error**	**User's accuracy (± 95% CI)**	**Producer's accuracy**
Deciduous to ERC	**0.0307**	4700	733	16%	0.81 (± 0.09)	0.88
Non-forest to ERC	**0.0123**	1887	173	9%	0.87 (± 0.08)	0.99
ERC lost	**0.0034**	516	71	14%	0.81 (± 0.09)	0.95
ERC stable	**0.0106**	1628	129	8%	0.89 (± 0.07)	0.99
Deciduous stable	**0.1709**	26134	4616	18%	0.95 (± 0.04)	0.75
Other	**0.7720**	118062	4572	4%	0.95 (± 0.04)	0.99
Overall accuracy				**0.95 (± 0.03)**		

Table 5-19. Thirty Year ERC change within the three study areas

Study Area	ERC cover 1986	ERC cover 2017	ERC increase		
			Area	Percent	Into deciduous forests
	---------------- acres (ac) ----------------			-------------- (%) --------------	
Tuttle Creek	4774	11403	6629	139%	48%
Perry Lake	1200	7670	6470	539%	56%
Bourbon N.	2144	8215	6071	283%	71%

All ERC cover and percent changes presented here are calculated based on the unbiased estimates of area presented in tables 12, 15 and 18

Appendix A - Field Work Photos

Figure A- 1. The field experiments in chapter 3 and 4 were carried out at the Howe Natural Resources Education Center

Figure A- 2. The project was partially funded through the National Wild Turkey Federation (NWTF) Super Funds. The prescribed burn treatments were administered by the Kansas Forest Service.

Figure A- 3. Center of circular permanent data collection plots were marked with a t-post color-coded by the compartment

Figure A- 4. Two microplots were established at each circular plot, located at 18.5 ft. from plot center, on bearings of 90 degrees (east) and 270 degrees (west)

Figure A- 5. Increment-core samples from 15 chinquapin oak (*Quercus muhlenbergii*) trees were collected to assess site index

Figure A- 6. The thinning treatment was conducted in spring 2015 with the prescription of: remove 25 trees/acre, mainly Eastern redcedar (*Juniperus virginiana*), American elm (*Ulmas americana*), hackberry (*Celtis occidentalis*), and Eastern redbud (*Cecis Canadensis*); and 50 stems of saplings/acre of American elm, Eastern redbud, Eastern redcedar and hackberry. Saplings were completely cut and treated with a chemical mix to suppress re-sprouting, and trees were single girdled

Figure A- 7. Thinned Eastern redcedar trees were left on the ground to facilitate the prescribed burn treatment

Figure A- 8. Fire behavior was mild in most places with 6-12 in. flame length and 5-10ft./ min rate of spread. This fire behavior was observed throughout burn only (B) compartments

Figure A- 9. In burn and thin (BT) compartments, pockets of cut 10-hr and 100-hr fuel, especially, cut Eastern redcedar trees caused flare-ups of 5-20 ft. flame height, with no impact on spread rate

Figure A- 10. Burn treatment was successful and no green vegetation in the understory was left behind

Figure A- 12. Immediately before the fire. Green vegetation in the understory is visible

Figure A- 11. Immediately after the fire. No green vegetation is visible

Figure A- 13. A transect established for fuel load (FL) inventory

Figure A- 14. Based on its diameter size class, the downed woody debris (DWD) were tallied in the standard fuel size classes of 1-hr, (0 to 0.25 in.) 10-hr (0.25 to 1.0 in.), 100-hr (1.0 to 3.0 in.) and 1000-hr (greater than 3.0 in.) fuels.

Figure A- 15. Depth of the litter/duff profile down to the mineral soil, and proportion of litter depth within the profile were measured

Figure A- 16. Canopy cover measurements were done using a GRS densiometer, along a transect placed at 90 degrees (east) and 270 degrees (west) from plot center

Figure A- 17. A tagged chinquapin oak (left) and eastern redbud (right) seedling. Approximately 20-25 seedlings per species (chinquapin oak and eastern redbud), within each compartment were tagged to assess immediate effects of the burn treatments on seedlings.

Figure A- 18. Oak seedlings that were top-killed by the burn, but re-sprouted following the burn

Figure A- 19. A chinquapin oak (left) and an Eastern redbud sapling, sprouting from the base after getting top-killed by the fire treatment

Figure A- 20. Two years after the thinning treatment, the girdled trees are either completely fallen or standing dead

Figure A- 21. Gaps in the overstory were observed two years post-thinning, due to fallen and dead trees in compartments that received a thinning treatment.

Figure A- 22. Quadrat sampling of the understory vegetation

Figure A- 23. Quadrat sampling of the forest floor (litter and duff layer), after clipping off the vegetation

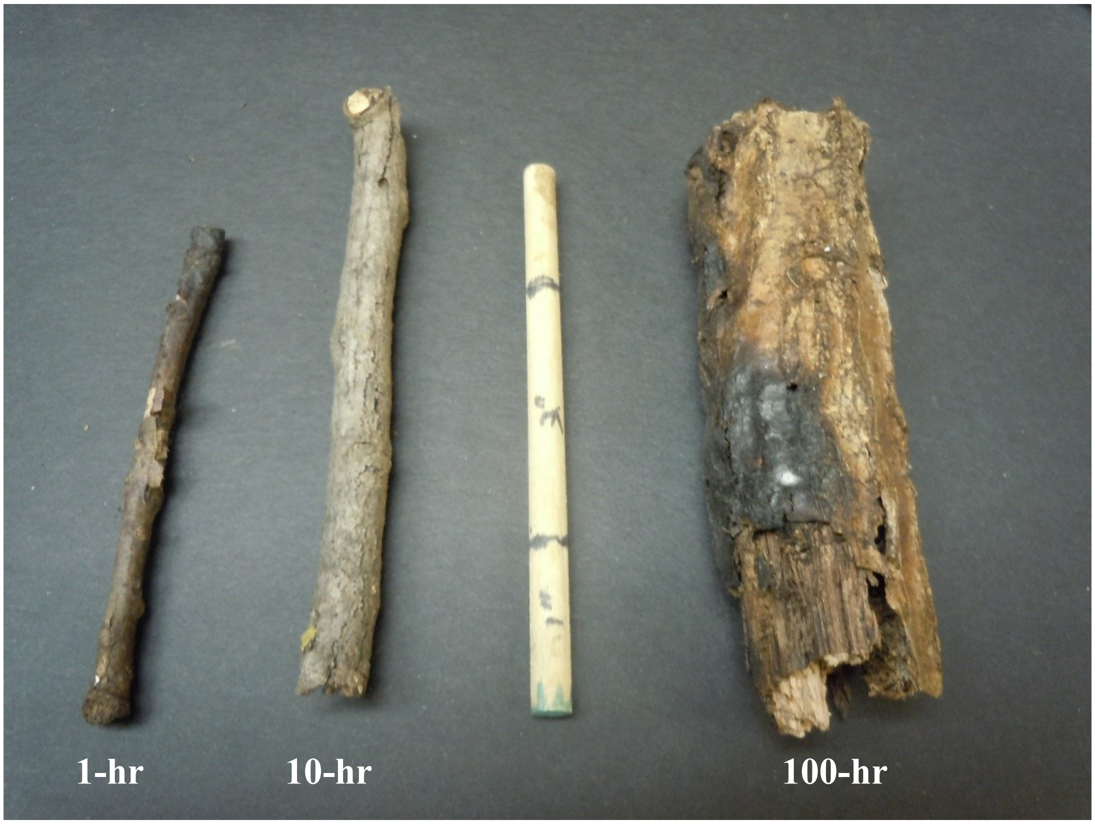


Figure A- 24. Standard fuel size classes of 1-hr, 10-hr and 100-hr

Figure A- 25. Litter (left) and duff (right) sorted out from the forest floor samples

Appendix B - Inventory Sheets

Inventory Sheet

Mgt area size (A):

# of plots (n):
(1/ac for areas of 30 ac or less; > 30 ac, then 24 plots + 1 addtnl for every 5ac)

Distance btwn plots:
$D=208.71\sqrt{(A/n)}$:

Date:

Plot # ________

GPS Coordinates:

Aspect (degrees):

BA:

(1/10 ac: 37.2 ft radius)

(> 5.0" DBH)

Spp.	DBH	Notes (health, damage, etc)

B- 1. Main inventory sheet for vegetation (at circular plots) - trees

microplot (1/100 ac: 11.8 ft radius at 90 degrees, 18.5 ft from plot center)

(1.0" DBH - 4.9" DBH)

Spp.	**DBH**	**Notes (health, damage, etc)**

seedlings in microplot (1/300 ac: 6.8 ft radius at 90 degrees, 18.5 ft from plot center)

Tree spp.	**# (1.0 ft tall for decid; 0.5 ft for conif.)**

Site Index (2 trees per mgt area) - Trees should be healthy and look to have been dominant for most of their life

Spp.	**DBH**	**Height**	**Age**
1)			
2)			

B- 2. Main inventory sheet for vegetation (at circular plots) – saplings and seedlings

Forest Understory & Canopy Cover

Date:

Plot No. __________

GPS Coordinates (Plot Centre) ______________________________________

Sample Location (sample frame) from plot center 1. ____________________ **2.** _______________________

Sample No.	Total fresh weight (g)	Total dry weight (g)

Cardinal direction	Canopy Cover (Yes- hit a canopy, No – No canopy)		Shrubs (Yes – Hit a shrub / No – No shrub)	
	Yes	No	Yes	No
50 ft E				
50 ft W				
Plot centre				

- On each direction (E & W), start at 5ft from plot Centre and collect data every 5ft ; final point 50ft.
- Numbering; 1. 5ft, 2. 10ft, 3. 15ft, 4. 20ft, 5. 25ft, 6. 30ft, 7. 35ft, 8. 40ft, 9. 45ft, 10. 50 ft

notes	herbaceous (Yes – Hit / No – No hit)	
	Yes	No

B- 3. Forest understory and canopy cover measurements

2017 - Seedling tagging study

Date: **Plot ID:** **GPS Coordinates:**

Tree DBH range 1”-6” more in the smaller range
Seedlings (<1”) Caliper – dia 1” above ground: DBH to the nearest 0.1”

Species	Size Class	No.	Azimuth	Distance (from plot center)	DBH (nearest 0.1”)	Height	Clump / Single	No. of sprouts
Chinkapin oak / Bur oak	**Tree** DBH range 1”-6” more in the smaller range	A1						
		A2						
		A3						
		A4						
		A5						
		A6						
	Seedling (<1.0”) Caliper – dia 1” above ground	A7						
		A8						
		A9						
		A10						
		A11						
		A12						

e. Redbud / A. Elm / Hackberry	**Tree** DBH range 1”-6” more in the smaller range	B1						
		B2						
		B3						
		B4						
		B5						
		B6						
Dominant Competitive spp								
	Seedling (<1.0”) Caliper – dia 1” above ground	B7						
		B8						
		B9						
		B10						
		B11						
		B12						

B- 4. Inventory sheet for the tagged seedlings study

Fuel Load (FL) Form

FL Page _ _ of _ _

Measurement Distances ft / m	Field 1 1-hour	Field 2 10-hr	Field 3 100-hr	Field 4 1000-hr	Field 5 # of Transects

Plot Key

RegistrationID: _ _ _ _
ProjectID: _ _ _ _ _ _ _ _
PlotID: _ _ _
Date: _ _/_ _/_ _ _ _

FL Table 1 - Fine Woody Debris (<3in / <8cm) - Duff & Litter

Field 6 Transect Number	Field 7 Slope %	Field 8 1-hr	Field 9 10-hr	Field 10 100-hr	Field 11 Duff/Litter Depth 1 (in/cm)	Field 12 Litter % 1	Field 13 Duff/Litter Depth 2 (in/cm)	Field 14 Litter % 2	Field 15 Local Code
1									
2									
3									
4									
5									
6									
7									

Notes/Dot Tally Space:

Crew:

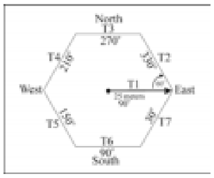
FL Table 2 - Coarse Woody Debris (>3in / >8cm)

Field 16 Transect Number	Field 17 Log Number	Field 18 Diameter (in/cm)	Field 19 Decay Class	Field 20 Local Code	Field 16 Transect Number	Field 17 Log Number	Field 18 Diameter (in/cm)	Field 19 Decay Class	Field 20 Local Code

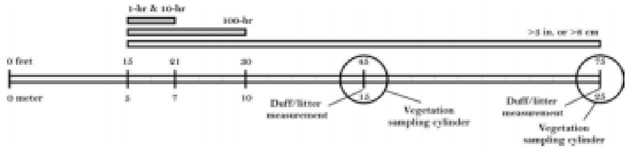
B- 5. Fuel loading (FL) form - FIREMON sapling form (https://www.frames.gov/partner-sites/firemon/sampling-methods/)

FIREMON FL Cheat Sheet

Plot layout



Sampling plane layout



Cover Classes

Class	Cover
Code	Canopy cover
0	Zero percent canopy cover
0.5	>0-1 percent of canopy cover
3	>1-5 percent canopy cover
10	>5-15 percent canopy cover
20	>15-25 percent canopy cover
30	>25-35 percent canopy cover
40	>35-45 percent canopy cover
50	>45-55 percent canopy cover
60	>55-65 percent canopy cover
70	>65-75 percent canopy cover
80	>75-85 percent canopy cover

Piece Sizes

Dead Woody Class			Piece Diameter (in.)
DWD	FWD	1-hr	0 to 0.25
		10-hr	0.25 to 1.0
		100-hr	1.0 to 3.0
	CWD	1000-hr and greater	3.0 and greater

CWD Decay Class

Decay Class	Description
1	All bark is intact. All but the smallest twigs are present. Old needles probably still present. Hard when kicked
2	Some bark is missing, as are many of the smaller branches. No old needles still on branches. Hard when kicked
3	Most of the bark is missing and most of the branches less than 1 in. in diameter also missing. Still hard when kicked
4	Looks like a class 3 log but the sapwood is rotten. Sounds hollow when kicked and you can probably remove wood from the outside with your boot. Pronounced sagging if suspended for even moderate distances.
5	Entire log is in contact with the ground. Easy to kick apart but most of the piece is above the general level of the adjacent ground. If the central axis of the piece lies in or below the duff layer then it should not be included in the CWD sampling as these pieces act more like duff than wood when burned.

Task list

	Crew member - task number		
Task	Recorder	Sampler 1	Sampler2
Organize materials	1		
Layout tape		1 (guider)	1 (guidee)
Measure slope	2 (record data)	2	2
Count FWD	3 (record data)	3	
Measure duff/litter and veg. at 75-foot mark	4 (record data)		3
Measure CWD	5 (record data)		4
Measure duff/litter and veg. at 45-foot mark	6 (record data)	4	
Check for complete forms	7		
Collect equipment		5	5

Precision

Component	Standard
Slope	±5 percent
FWD	±3 percent
CWD diameter	±0.5 in./1 cm
CWD decay class	±1 class
Duff/litter depth	±0.1 in./0.2 cm
Percent litter estimation	±10 percent
Vegetation cover estimation	±1 class
Vegetation height estimation	±0.5 ft/0.2 m

B- 6. FIREMON FL cheat sheet – (https://www.frames.gov/documents/projects/firemon/FLv3_Cheatsheet.pdf)

Appendix C - Site Index Curve

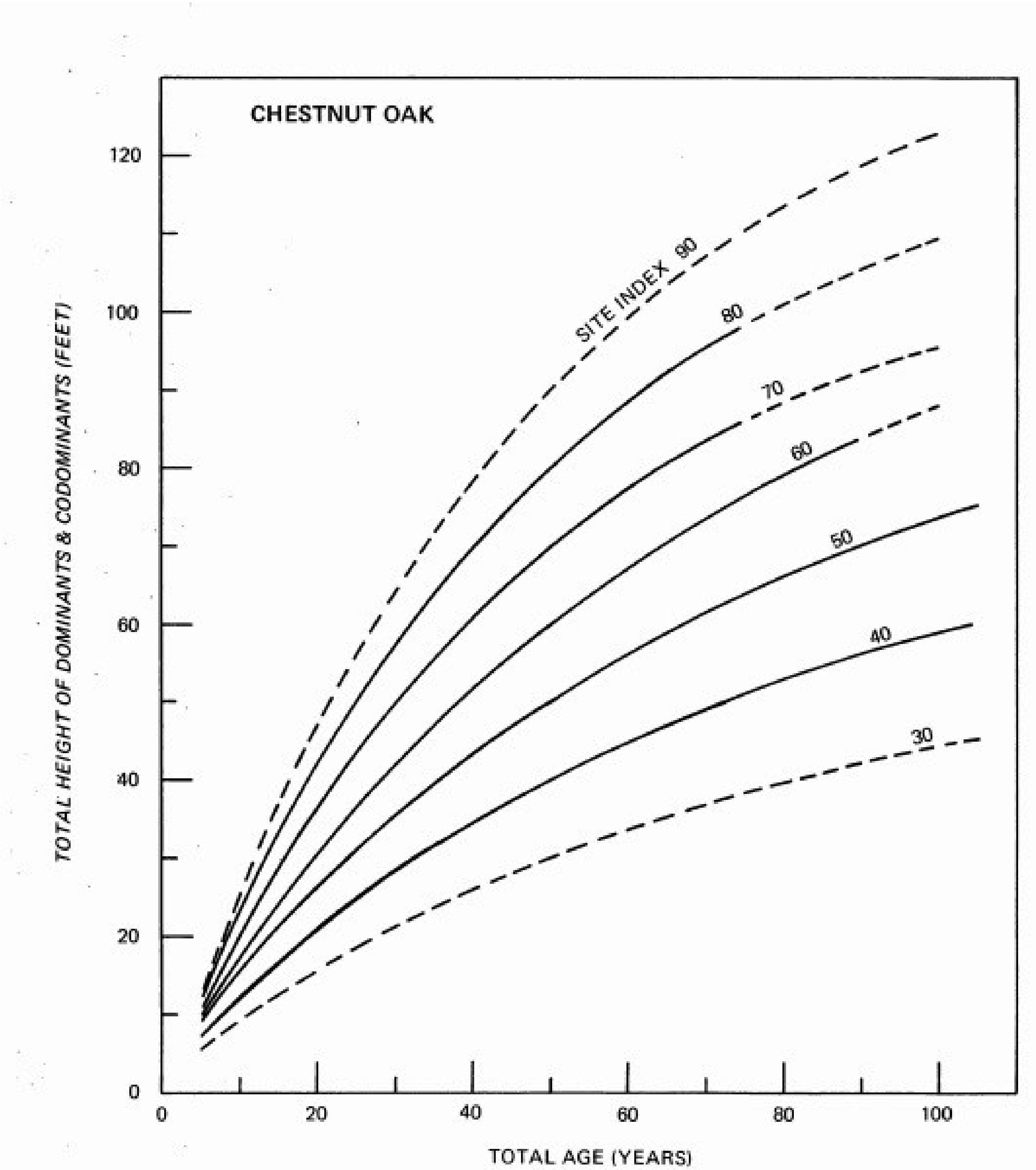


Figure C-1. Site index curves for chestnut oak in the Central States (Carmen, 1971)

Appendix D - Stocking Diagram

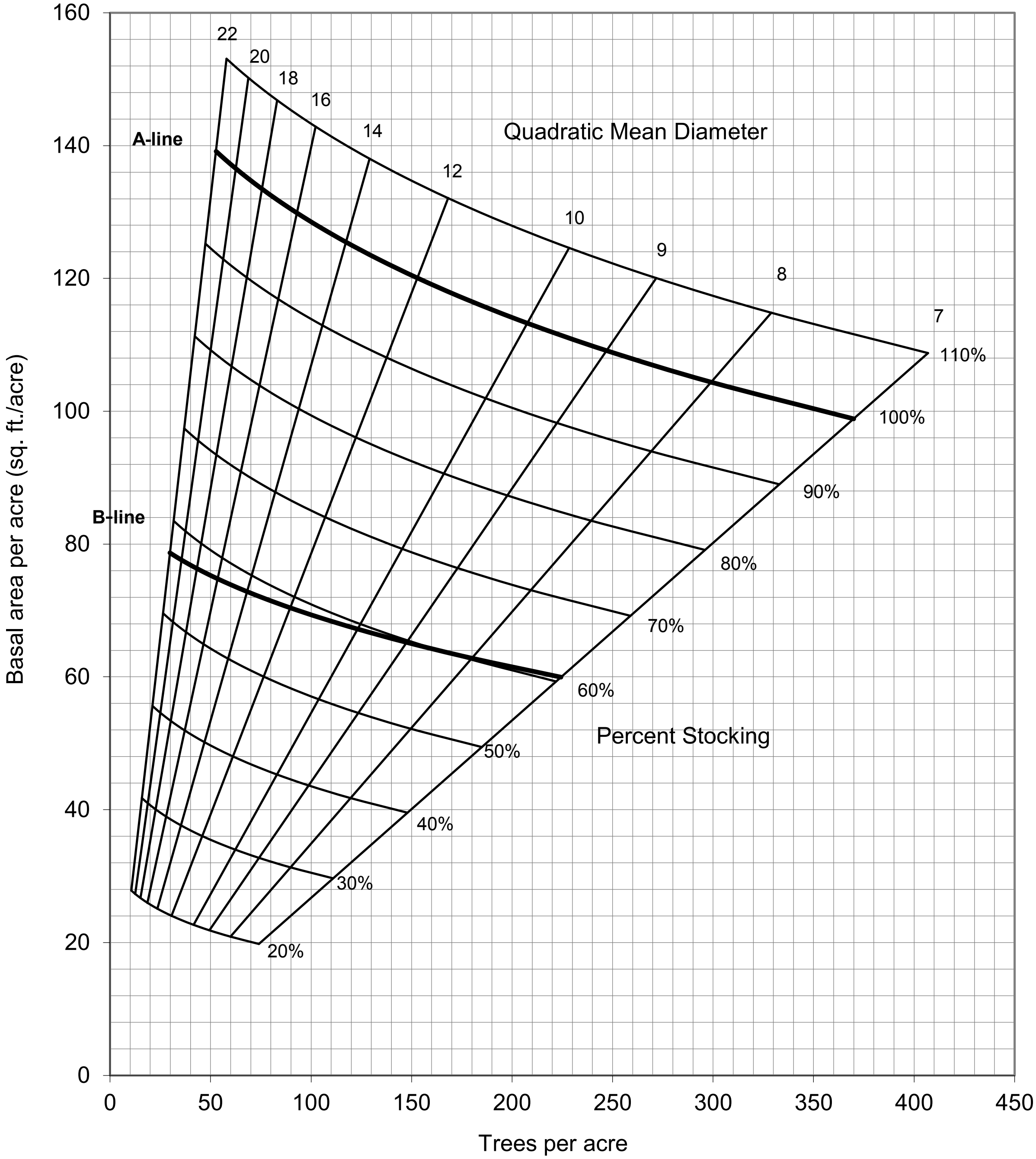


Figure D-1. Gingrich Stocking Diagram - (http://oak.snr.missouri.edu/silviculture/tools/gingrich.html)

Appendix E - Workflows for Chapter 5

Accuracy assessment used to compare different classification approaches

In this classification, we have 6 land cover classes;

1. Agricultural lands
2. Grasslands
3. Deciduous woodlands
4. Eastern redcedar
5. Water
6. Wetlands

Rule of thumb: to have at least 10 times the number of classes, as test pixels for each class. Therefore, at a minimum each class should have 60 test pixels. Total of 360 test pixels.

1. In *ArcMap* open the pre-classification image
2. Go to *ArcCatalog,* select a folder and create a new shapefile "*Reference_points*" with "*points*" as feature type.
3. Before adding points to the shapefile, add two fields into the attribute table of the shapefile.

   Add Field –

   - First field is "*Land cover*" with "*text"* type
   - Second field is *"class"* with "*short integer"*
4. Next, to add points use the "*Editor"* toolbar. Start editing and select the "*Reference points",* and in the construction tools window select *"points*".
   - Make sure the editing is being done on the pre-classification image, and zoom in appropriately to make sure the point is being placed properly in the targeted pixel

- During the same time, add required information into the attribute table, that's why we added a text and a number column.
- The class number in the attribute table for each class should match the class numbers in the classified images.
- Therefore, it is important to maintain the same order in the classification images as well as in the test data (the above-mentioned order).

5. For better accuracy, we can open the NAIP imagery (1 m resolution) in ArcMap and switch between the images to identify the land cover class. (sometimes it is confusing to distinguish between agriculture lands, deciduous forests and grasslands).
6. For 1986 images compare with google earth pro
7. When adding information to the attribute table, it is easy to use "*select by attribute"* and choose land cover from dialog box
    - Select all the points for that particular class, right click land cover column and select field calculator.
    - Select "land cover" and = "Agriculture" for the first class, and all the points for this class will have this class name
    - Once all the points were selected, save edits
    - In the attribute tables "class" column give the corresponding class number
8. Before proceeding to the next step we need to import the classified image.
    - However, the ENVI classified image is in raster format and needs to be converted to a vector in order to be used in ArcGIS environment.
    - When doing so make sure not to select the "unclassified" class
    - This will create an .evf file, and then convert it to a shape file.

- In ArcMap, convert this shapefile into a raster (after applying all the classes from symbology).
- Open the attribute table of this created raster file, add a classification field and give each class a number (same as we used in the reference points).

9. Next, need to align the reference points with the pixels of the classification image
   - "*Geoprocessing*" tab, - *environments – processing extents* - and fill in the extent as the classified raster, set the snap raster to classified raster too.
10. Enable spatial analyst extension
11. Now convert reference points to reference pixels.
    - Search for "*point to raster*" in arc toolbox
    - Select, input feature – "Reference points" shape file, and "class" value field
    - Make sure the cell size is 30 (as we are using Landsat)
12. Next, the reference points and the classified image will be combined
    - In Arc toolbox, *spatial analyst – local – "combine"*.
13. To create the confusion matrix;
    - First export the "combined" table as a .dbase table, then open pivot table tool in arc toolbox
    - Input table is the table just exported, select the classified raster field as the input and the reference points as the pivot field. Value field will be the count. OK
14. From this point forward, will use excel
    - Export the table/matrix as a txt file.
    - In excel, open the txt file and select delimited, hit next and select comma delimited, then next and next.

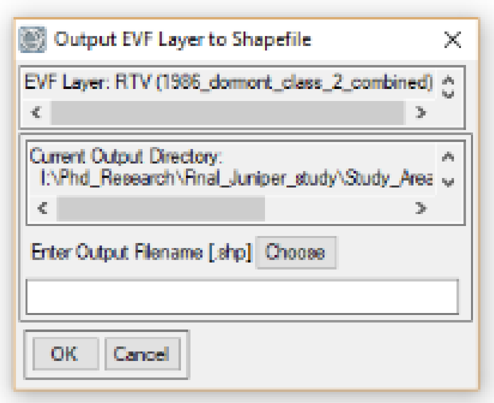
15. Edit the matrix. Add class names etc..

- Add the formulas to measure, Kappa coefficient, overall accuracies, class accuracies, commission, and omission.
- Add a row to find total amount of pixels for each class

Generating the final Change Map

First, we need to convert the classification image into a ArcMap compatible form to use it in ArcMap to generate the change map

1. Use Classification to Vector tool to convert the classified image into a vector file (EVF)
2. Use classic EVF to shapefile tool to create the shapefile

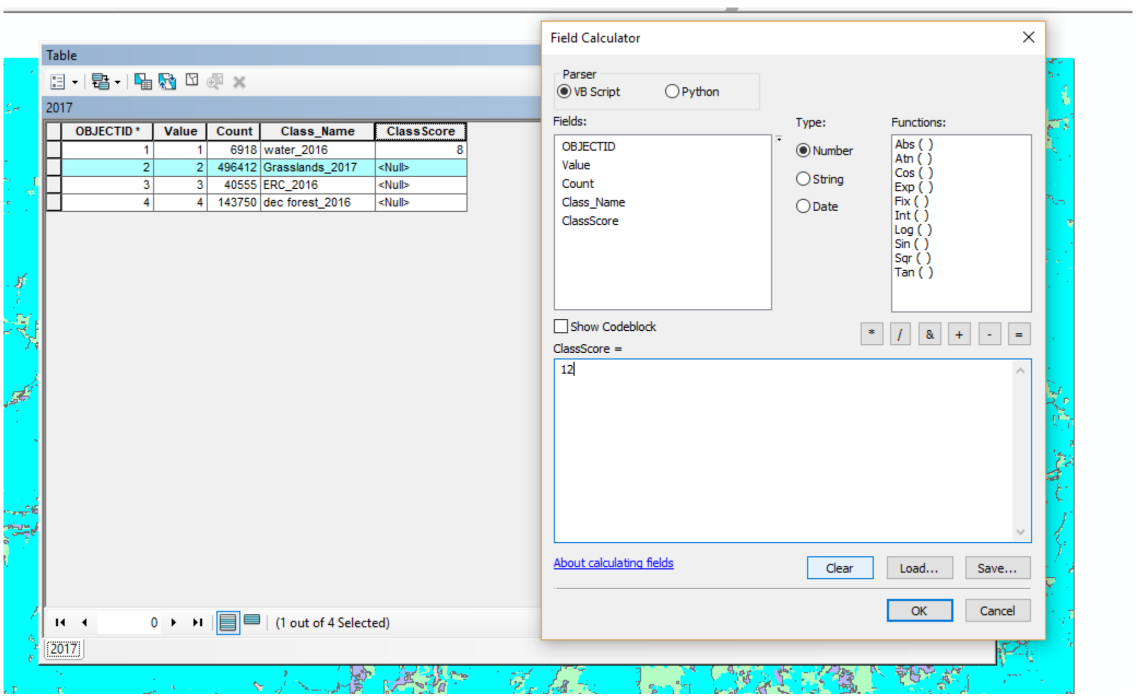


3. Import the shapefile into ArcMap
4. Open symbology, show categories, unique values and press add all values. Un-check the "all other values"
5. Use "feature to Raster" tool to convert the shapefile into a raster. Select the shapefile and, change the output cell size to 30 (since we are using Landsat imagery)
6. Open the attribute table of the generated raster file and "add a field"

- Name the new field as "Class Score"

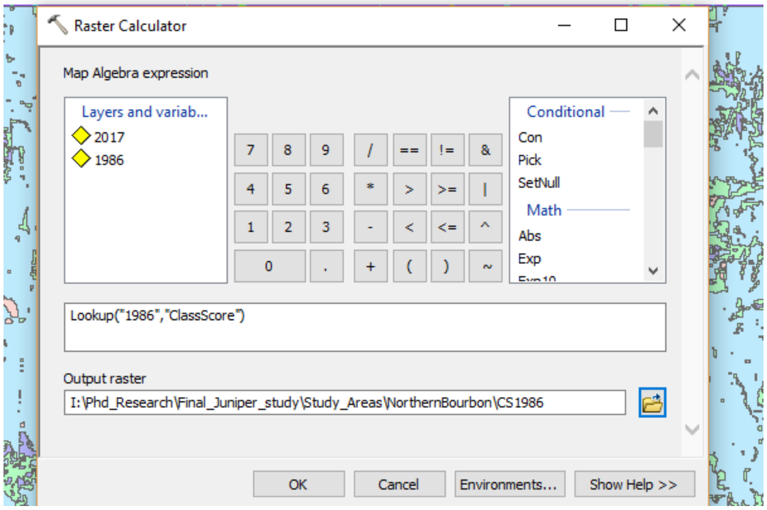
- Use field calculator to add the following class scores for the 1986 and 2017 classified images

Class	1986	2017
ERC	0	0
Deciduous	1	4
Water	2	8
agric/grassland	4	12



7. Use raster calculator tool to generate raster file each for 1986 and 2017 with the class scores added to the value field

   Use the expression: Lookup("1986 Class Score")



8. Then use the raster calculator again to generate a difference map by the expression :

   "CS2017" – "CS1986"

- This will generate a map with values ranging from -3 to +12 (following table).

  Therefore, reclassify tool need to be used to generate the final change map.

9. Using the reclassified tool, the generate the final change map by combining change classes per the following table

- The 6 classes in the final change map are;

  1. Deciduous to ERC
  2. Non-forest vegetation (agric/grasslands) to ERC
  3. ERC lost
  4. ERC stable
  5. Deciduous stable
  6. All other

Value	Change	Reclassified class
-3	Agric/grasslands to ERC	2
-2	Water to ERC	2
-1	Deciduous to ERC	1
0	ERC unchanged	4
1	Agric/grassland to Deciduous	6
2	Water to Deciduous	6
3	Deciduous unchanged	5
4	ERC to Deciduous	3
5	Agric/grassland to water	6
6	Water unchanged	6
7	Deciduous water	6
8	ERC to water	3
9	Agric/grasslands stable	6
10	Water to agric/grasslands	6
11	Deciduous to agric/grasslands	6
12	ERC to agric/grasslands	3

10. To visualize the change map consistently, the following color panel was used.
    1. Deciduous to ERC – black
    2. Non-forest to ERC – Ginger pink
    3. ERC lost – Chryoprase
    4. ERC stable – Tuscan red
    5. Deciduous stable – Fir green
    6. All other-Sahara sand

Accuracy Assessment of final change maps

The accuracy assessment for the change maps will be different than the previously explained method. We follow the standard accuracy assessment practice guidelines of Olofsson et al. 2014.

The excel document provides details on deciding on the size of the sample;

1. Use the method described in the above manuscript to determine the number of samples needed. A stratified random sampling procedure is followed

- Following table shows the number of random samples required from each class;

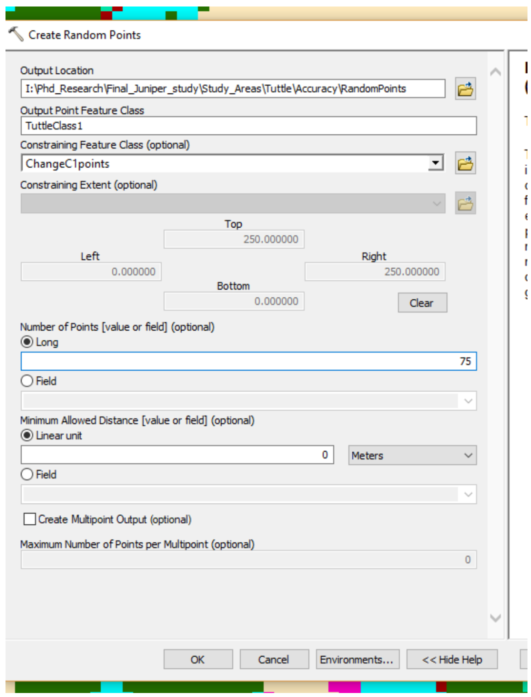
Change class	Tuttle	Perry Lake	Northern Bourbon
1	75	75	75
2	75	75	75
3	75	75	75
4	75	75	75
5	100	100	100
6	131	125	128
Total	531	525	528

Generating a random sample of points per each class;

1. Open the change map in ArcMap, and select one of the change classes.

- This will select all the areas in the map corresponding to that particular change class

2. Now use raster to point tool from ArcToolbox to create a point feature class for that particular change class.
3. Open "Create Random Points" tool and select the created points feature class as the constraining feature class to generate the specified amount of random points for that class



4. Repeat the above procedure to draw random points for each class, in each change map.
5. Open the two Landsat images for 1986 and 2017, along with available high resolution aerial imagery to compare the land class specified in the random points with the ground-truth imagery.
6. Record the response in excel sheets and construct the error matrix as described in the above mentioned accuracy assessment workflow.