THE NEXT GENERATION OF LAND SYSTEM SCIENCE: INTEGRATING MESO-SCALE ANALYSIS AND UAS REMOTE SENSING IN CHANGING PLANT COMMUNITIES OF THE UNITED STATES' SOUTHERN GREAT PLAINS

By

AUSTIN L. BOARDMAN

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The University of Tulsa

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Thesis Approved:

Dr. Jacqueline Vadjunec

Thesis Adviser

Dr. Adam Mathews

Dr. Bruce Hoagland

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Abstract: As concerns about desertification, climate change, economic pressures, and reductions in global biodiversity become more prevalent, so too does the importance of research in the socio-ecological resilience of dryland agricultural communities. Cimarron County, Oklahoma and Union County, New Mexico have historically faced cyclical drought and land degradation as a challenge to agriculture. More recently, the expansion of woody plant species in rangelands threatens to destabilize grassland communities, limit forage for cattle, and reduce water resources. This thesis uses a Land System Science (LSS) approach to study how vegetation communities have changed in the two counties across multiple scales. By utilizing household surveys with ranchers, ground-level biodiversity and rangeland health assessments, UAS imagery, and satellite-based remote sensing, a holistic, integrative picture of the interrelated factors affecting woody plant encroachment (WPE) is presented. Household surveys indicated that agriculturalists are keenly aware of nuisance species on their property, with many taking actions to reduce their abundance. Woody species cited by landowners including one-seed juniper, Great Plains yucca, broom snakeweed, and cane cholla were reliably detected and identified to species level through ground and UAS observations. While there was strong agreement in land-cover estimates between the two methods, ground observations were more useful in measuring herbaceous species biodiversity while UAS was advantageous in surveying woody species across larger areas. WPE was affected by land-use factors, and was more severe in grazed pastures. By contrast, WPE was less severe on Conservation Reserve Program lands and plots with prior herbicide applications. Environmental factors also played a role, with greater WPE vulnerability in areas of rugged terrain, sandy soils, and cooler, drier climates. While LSS research has a history of using both field observations and satellite remote sensing to connect "people to pixels," the present investigation demonstrates of the utility of UAS imagery as a powerful bridge in scale. As studies in land systems evolve and become more important, UAS is poised to serve as a potential rapid assessment method which can provide context and additional detail to coarser- or finer-scale analyses.

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CHAPTER I

INTRODUCTION

Desertification of grasslands and changes in vegetation composition have been observed globally in recent decades (Geist and Lambin 2004; Leis et al. 2017; Robert et al. 2002). However, these phenomena, often studied at local and/or regional scales, are not fully understood (Reynolds and Stafford Smith 2002). In one such region, the Southern Great Plains of the United States, agriculturalists of Cimarron County, Oklahoma and Union County, New Mexico have encountered increasing land degradation, particularly in the form of woody plant encroachment. At the same time, ranching and farming (henceforth, agriculture) in this community serves as the foundation of the economy (USDA 2012b, 2012a; Vadjunec and Sheehan 2010), with agriculturalists exhibiting a history of resilience and grit in the face of repeated "natural" disasters and extreme weather events. Most prevalent among these disasters are the Dust Bowl of the 1930 which caused severe soil erosion as well as subsequent cyclical drought events (Cordova and Porter 2015; SCCSC 2013; Wenger, Vadjunec, and Fagin 2017).

Presently, woody plant encroachment (WPE) in grasslands is emerging as a significant hazard facing the region, with researchers and landowners observing increases in the abundance and extent of trees and shrubs such as walking stick cholla, one-seed juniper, saltcedar, and mesquite (Fagin et al. 2016). Research in other systems has shown that increases in woody vegetation can suppress native herbaceous vegetation (Lett and Knapp 2005), reduce forage for livestock grazing (Scholes and Archer 1997), disrupt nutrient cycling (Satti et al. 2003), intercept water resources (Scott et al. 2006), and promote soil erosion (Parizek, Rostagno, and Sottini 2002). Therefore, WPE in an agricultural area such as the Southern Great Plains is likely to have both biophysical and socioeconomic impacts. Meanwhile, little consensus exists regarding the causes of WPE. While environmental factors such as climate and soil are undoubtedly influential drivers in a changing landscape (Archer, Schimel, and Holland 1995), substantial evidence also implicates land-use behaviors, such as fire suppression and overgrazing, as causes of WPE (Ganguli et al. 2011; Bragg and Hulbert 1976).

Previous research on WPE has employed approaches as varied as the causes and consequences of the problem itself (e.g., Jeltsch et al. 1997; Knapp et al. 2008; Lubetkin, Westerling, and Kueppers 2017). Despite this, few studies have synthesized multiple streams of data to examine the effects of synergistic factors. Analyses are often performed at a single scale, typically through ground-level observations or satellite remote sensing (see Allen and Allen 1991; Laliberte et al. 2004). Further, social science and ethnographic methods are rarely utilized despite the clear implications for landowners and stakeholders (though see Dalle, Maass, and Isselstein 2006; Hudak, Wessman, and Seastedt 2003). As a result, the current literature on changing plant communities tends to raise more questions than it answers.

The present investigation, by contrast, seeks to gain a more holistic picture of the factors influencing vegetation communities in the Southern Great Plains (SGP). Specifically, this study seeks to directly answer the following three questions:

1. How does woody plant encroachment vary across different environmental gradients, land-use/management practices, and sociopolitical boundaries?

2. What is the relationship between herbaceous plant biodiversity and woody plant encroachment? How does it vary across scales?
3. What are the benefits and limitations of multiple scales of analysis, particularly considering the potential role of unmanned aerial systems (UAS) as a scalar bridge in rapid vegetation assessments?

Given the consequences of unmitigated WPE to the ecological integrity of grasslands in the SGP, as well as the threat to the livelihoods of farmers and ranchers in the region, research in this area is as necessary as it is timely. Past National Science Foundation (NSF) research by Vadjunec and colleagues (2018) illustrates socio-ecological system resilience and sustainability challenges in the region. Relatedly, a five-year USDA funded initiative is currently seeking to help agriculturalists in southeastern Colorado, northeastern New Mexico, and the Oklahoma panhandle increase their resilience to climate variability, loss of groundwater, and other hazards (Ganguli et al. 2018). As part of these larger funded projects, this thesis seeks to understand the relationship between landowner perceptions and management actions as they impact herbaceous and woody plant biodiversity in the study area. More specifically, this study's participatory approach draws on land use and management surveys, ground-level biodiversity inventories, UAS imagery, and satellite remote sensing to identify factors affecting vegetation on rangelands as part of the larger, on-going research project..

This thesis is structured in a traditional five-chapter format. Chapter 1 (Introduction) delivers an overview of previous research on WPE, including its associated land management practices and environmental contributors, as well as impacts associated with changes in plant communities. Additionally, a brief description of the two-county study area, comprised of Union County, New Mexico and Cimarron County, Oklahoma, along with its historical context is presented. In Chapter 2 (Literature Review and Theoretical Framework), the field of land system science is introduced, with detailed discussion of its implications on land degradation, landowner decision-making, and remote sensing. Additionally, the chapter discusses biodiversity and the ways scale can influence findings in geographic research. Chapter 3 (Methodologies) details the tools and approaches utilized in this thesis. Among these methods are satellite detection of WPE through the National Land Cover Dataset, UAS imagery classification, ground-level vegetation sampling, and household surveys with agriculturalists. Additionally, Chapter 3 explains the synthesis of these methods used to triangulate the complex factors associated with land degradation. Chapter 4 (Results and Discussion) discusses the findings of each methodology and explores implications for landowners and LSS practitioners alike. Finally, Chapter 5 (Conclusion) summarizes this research, discusses the scope and limitations of the study, and lists some potential future directions for investigation.

Woody Plant Encroachment (WPE)

The increase in the extent, density, and hazards associated with trees and shrubs encroaching on grassland habitats globally, known as woody plant encroachment (WPE), has been cited as a concern for agriculturalists, academics, water managers, and ecologists alike (Alofs and Fowler 2013; Archer, Schimel, and Holland 1995). WPE exacerbates environmental issues such as loss of biodiversity (Naeem 2002), reduced streamflow (Zou, Qiao, and Wilcox 2016) and groundwater (Ansley 2005), and degradation of grazing land (Anadón et al. 2014). Further, those who face the greatest risk from WPE are likely also those who are most readily able to reduce the effects through land-use practices. Thus, WPE is closely tied to land degradation theory presented by Blaikie and Brookfield (1987), Turner, Lambin, and Reenberg (2007), and others, wherein landscape changes may directly affect agriculture and present complications to landowner decision-making. Specifically, land-use behaviors such as fire suppression (Ratajczak et al. 2014) and overgrazing (Oztas, Koc, and Comakli 2003) have been closely associated with land degradation. As this section continues, a summary of WPE-associated land-use practices is provided, followed by an overview of the impacts of tree and shrub encroachment.

Land Management Practices Associated with WPE

Among the most prominently cited land-use behaviors resulting in WPE is fire suppression, a practice in which natural and man-made fires are quickly extinguished upon discovery and prescribed burns are avoided due to perceived risk (Hudson 2011). Although fire is a natural occurrence to which grassland ecosystems are adapted (Collins and Wallace 1990), efforts to control fire in North America emerged upon European settlement (Fowler and Konopik 2007) and became more widespread as more lands fell under government management (North et al. 2015). As a result, grassland biodiversity has become reduced (Leach and Givnish 1996; Uys, Bond, and Everson 2004) and soil nutrient cycling has decreased (Boerner 1982), causing fire to become arguably the most important factor affecting vegetation communities (Bond and Keeley 2005).

Further, fire suppression in grasslands allows trees and shrubs to gain a foothold and grow to size and age classes that are not typical under natural fire regimes (Mairota et al. 2014; Twidwell et al. 2013). For example, Coop and Givnish (2007) analyzed over six decades of aerial photographs in the Valles Caldera of New Mexico to determine causes of WPE in the area. They found encroachment to be most severe in rugged terrain where fires cannot easily spread across the landscape, while valleys where regular fire was common had much less severe WPE.

Additionally, fire suppression can counterintuitively cause more severe fires by creating added fuel on the landscape (Baker 1992). For example, *Juniperus virginiana*, a closely related species to *Juniperus monosperma* found in this project's study area, has been implicated in extremely severe fire events because of its highly combustible oil content and its dense presence on the landscape (Weir and Scasta 2014). Similar conditions have resulted in abundant fuel which, when coupled with a changing climate, have dramatically increased fire severity in the West (Westerling et al. 2006). Further complicating the situation, many land managers view prescribed burns as too risky. Morton and colleagues (2010) found that roughly half of landowners surveyed in the Midwest thought of prescribed burns as a viable land management tool, though only 25% had participated one. In the West, given drier conditions and additional fuel on the landscape, landowners may be more reluctant to burn land in the future (Harr et al. 2014).

Grazing practices are also frequently cited as an important contributor to WPE (D' Odorico, Okin, and Bestelmeyer 2012; Watkinson and Ormerod 2001). Increased climate variability, economic pressures, and complicated land tenure regimes can force some land managers to periodically overgraze, resulting in rangeland degradation and potentially

WPE (Vadjunec and Sheehan 2010). Allen and Allen (1991) found that overgrazing creates open spaces in rangelands where fragments of *Cylindropuntia imbricata* (cane cholla—a key species of concern in the Southern Great Plains cited by Fagin and colleagues (2016)), can drop to the ground and propagate. Animals are commonly identified vectors of woody vegetation dispersal, including both livestock (Bartuszevige and Endress 2008; Radford et al. 2001; Tews, Schurr, and Jeltsch 2004) and birds associated with ranching operations (Coppedge et al. 2004). In addition to changing the physical structure of the grasslands by causing patchiness in the sod, overgrazing can also reduce herbaceous species biodiversity (McIntyre, Heard, and Martin 2003; Tallowin, Rook, and Rutter 2005).

WPE Impacts

While WPE can have negative effects on a number of different stakeholders, the greatest impact is likely to be felt by agriculturalists, especially ranchers experiencing reductions in forage. Even a 1% increase in woody vegetation can reduce forage for cattle and other livestock by more than 2.5% (Anadón et al. 2014, 12951), and in some systems has reduced forage by over 300% (Richter, Snyman, and Smit 2001, 106). Encroachment of woody plants can also directly suppress herbaceous plant productivity (Belay, Totland, and Moe 2013; Dalle, Maass, and Isselstein 2006; Lett and Knapp 2005), reduce herbaceous species richness (Clark et al. 2007; Ratajczak, Nippert, and Collins 2012), and lower nutrient availability (Hudak, Wessman, and Seastedt 2003; Satti et al. 2003), further compounding effects on ranchers. With agriculture serving as the main economic driver in the Union/Cimarron county study area, an increase in tree and shrub landcover would clearly raise questions regarding the sustainability of ranching operations (Wenger, Vadjunec, and Fagin 2017).

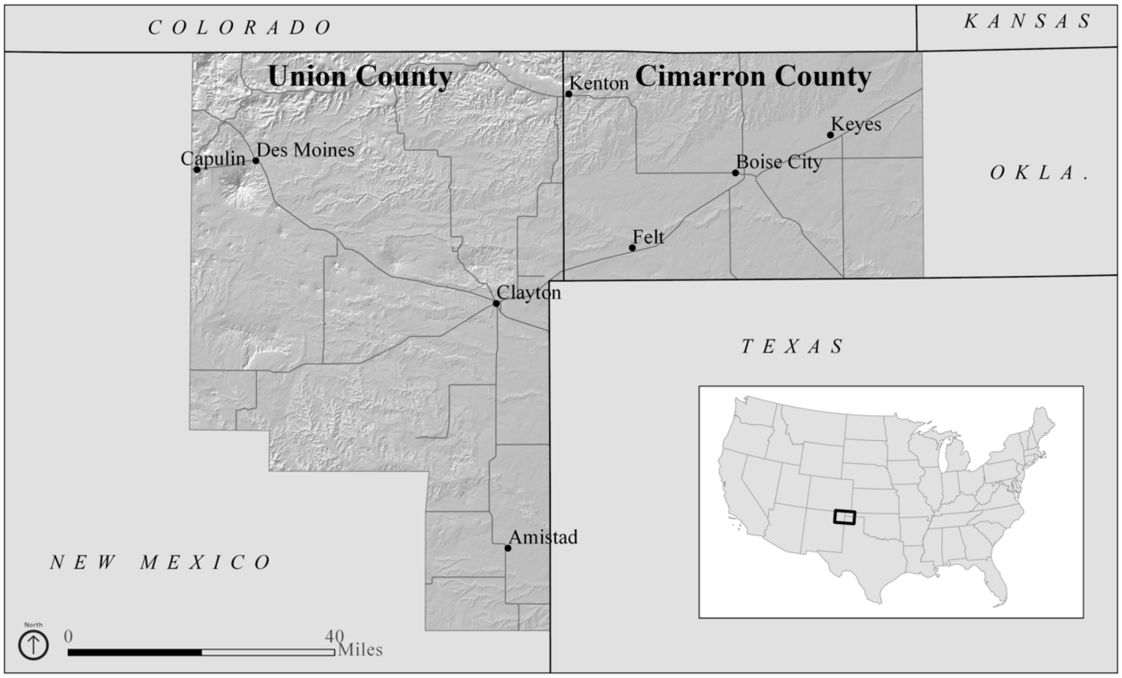
Beyond the impacts to forage, WPE will also negatively affect water resources, both for ranchers and farmers inside and outside of the region. The structure of woody plants such as juniper can intercept precipitation before it ever reaches the ground (Wilcox 2008). Water that does reach the ground is then less likely to infiltrate the soil in woody systems (Parizek, Rostagno, and Sottini 2002). Further, the large water budgets of trees and shrubs can cause wasteful evapotranspiration (Munson and Lauenroth 2012), with some species consuming or transpiring as much as 32 gallons of water per day (Mounsif 1992). As a result, soil salinity (Owens and Moore 2007) and erosion (Parizek, Rostagno, and Sottini 2002) has increased in some systems. Additionally, deep taproots in some plants such as mesquite and saltcedar can exploit valuable groundwater (Ansley 2005; Rundquist and Brookman 2007), potentially impacting downstream farmers reliant on irrigation (Wenger 2015). Zou, Qiao, and Wilcox (2016) modeled Oklahoma streamflow rates under hypothetical WPE regimes, examining how water levels in streams might change under an extreme, but not unrealistic scenario where rangelands in the area converted entirely to *Juniperus virginiana* coverage. The authors found that the resulting vegetation change would reduce water levels by up to 40% in the upper reaches of their study area, and an average of 20% throughout the entire basin (Zou, Qiao, and Wilcox 2016, 813-814). Remarkably, these changes were predicted to occur regardless of future climate change conditions. Considering these impacts, changing vegetation communities in the Southern Great Plains are poised to affect both local agriculturalists and downstream stakeholders.

Study Area

The geographic extent of this investigation includes two neighboring counties in the Southern Great Plains: Cimarron County, Oklahoma and Union County, New Mexico. A predominantly rural and agricultural landscape, the region is composed primarily of EPA Level III Ecoregion 9.4.1 (High Plains) marked by a cold semi-arid climate, shortgrass prairie, and terrain ranging from flat to rolling hills (EPA 2013; Hoekstra, Molnar, and Jennings 2010). Additionally, Ecoregion 9.4.3 (Southwestern Tablelands) is present along the region's northern edge, featuring vast basalt mesas and dry river gorges (Lewis and Richter 2015) and vegetation ranging from shortgrass prairie to sagebrush (EPA 2013). The elevation ranges from 8,707 ft in the west, at the peak of Mt. Capulin, to 2,400 ft toward the east (USGS 2015).

As the epicenter of the Dust Bowl of the 1930s, agriculturalists in the region have exhibited remarkable resilience in the face of natural hazards, with woody plant encroachment appearing to be a growing issue for the future (Egan 2006; Fagin et al. 2016; Vadjunec and Sheehan 2010). While the two counties share many biophysical and socioeconomic traits, land-use/land-cover change (LULCC) between the two counties has been variable both in terms of agricultural practices (Wenger, Vadjunec, and Fagin 2017) and vegetation (Fagin et al. 2016). As this section continues, a summary of the climate, socioeconomic structure, and vegetation of the study area is presented.

Figure 1: Map of Study Area



Data source: Created by the author using data from USGS State and County Boundaries (USGS 2014b, 2014a), USGS National Elevation Dataset (USGS 2016a), USGS Cities and Towns of the United States(USGS 2014c), USGS National Transportation Dataset (USGS 2016b).

Climate, Water Resources, and Drought

Climate in the region is generally cool, with average mean temperature highs of 72ºF and lows of 40ºF (Fick and Hijmans 2017). The area receives roughly 18 inches of precipitation annually (SCCSC 2013), most frequently in the form of short thunderstorms that move southeasterly, often becoming weaker in the eastern portions of Cimarron County (NCDC 2016). Winter precipitation often comes in the form of snow, providing crucial subsurface moisture for agriculturalists (Hughes and Robinson 1996). Small ephemeral snowpack can form, particularly along Johnson Mesa and Black Mesa to the north, much of which flows into the Dry Cimarron River valley (Trauger and Kelley 1987). A future of higher temperatures, reduced precipitation, and a smaller snowpack due to climate change is expected to strain agriculture in the region (Union of Concerned Scientists 2016).

Although many agriculturalists do rely on surface water (Rawling 2015), much of the region is hydrologically isolated from the snowpack of the Rocky Mountains by the Sierra Grande Arch and topographic boundaries near Mt. Capulin (Trauger and Kelley 1987; USGS 2016a). As a result, groundwater obtained from springs and wells is more widely used in the area than surface water (Wenger, Vadjunec, and Fagin 2017). Most landowners in Cimarron County can access the High Plains (Ogallala) Aquifer (HPA), while Union County is underlain by patches of the Dakota Sandstone, Morrison Formation, and HPA (Zeigler 2011). While HPA recharge comes primarily in the form of summer rain (Meixner et al. 2016), snowpack runoff from outside the topographic basin may be a more significant contributor to other formations (Trauger and Kelley 1987; Zeigler 2011).

Cyclical drought is an intrinsic trait of drylands (Allen et al. 2007) and the region has faced six major drought events in the past century (Vadjunec et al. 2018). The most infamous of these, the Dust Bowl of the 1930s, completely disrupted agriculture across the Southern Great Plains (Worster 2004), causing widespread dust storms and erosion of croplands (Lal, Reicosky, and Hanson 2007) forcing hundreds of thousands to leave the region (Gregory 1989). Another notable drought in the 1950s was called one of the most severe on record (Nace and Pluhowski 1965). Most recently, a drought lasting from 2000-2015 presented temperature and precipitation conditions that were at times even harsher than the Dust Bowl (U.S. Drought Monitor 2019). Agriculturalists in the region have naturally faced difficulty with production in the face of unreliable precipitation (Wilhite 1993).

Socioeconomic Influences

The socioeconomic landscape of the study area is primarily rural and agricultural. Cimarron County is Oklahoma's westernmost county, with a total area of 1,835 sq. mi (USCB 2018a). Its population has consistently decreased since its heyday in the 1930s, to a current level of 2,154 individuals, with 971 households (USCB 2018a). The population density is low, at 1.3 persons per square mile (USCB 2018a). In 2012, there were 554 farms in the county, covering 1,157,186 acres (98.5% of the entire county) (USDA 2012b). Of this, 63.3% was used as pastureland, helping to put Cimarron County among the top 3% of cattle producing counties in the nation (USDA 2012b). The remainder of agricultural land in the county is primarily cultivated; wheat, sorghum, and corn are the leading crops (USDA 2012b). While the former two crops may be grown dryland (without irrigation), farmers increasingly use center pivot irrigation (CPI) to help reduce vulnerability to drought or to enable cultivation of corn, which yields greater profits but requires large amounts of water (Wenger 2015). Between 1985 and 2013, the number of center pivot systems nearly doubled in Cimarron County, covering nearly 800,000 acres (Wenger, Vadjunec, and Fagin 2017, 10).

Union County occupies the northeastern corner of New Mexico and at 3,824 sq. mi. is substantially larger than Cimarron County, (USCB 2018b). Its population has also decreased, to a current total of 4,187, with 1,454 households (USCB 2018b). The population density is slightly lower than Cimarron County, with just 1.2 persons per square mile (USCB 2018b). Union County was home to 353 farms in 2012, accounting for 80.4% of the total county land (1,967,370 acres) (USDA 2012a). The county ranks in the top 6% of cattle producing counties in the U.S. (USDA 2012a). Agricultural land in Union County is largely dominated by rangeland (95.4% of all county agricultural land) (USDA 2012a). In contrast to Cimarron County, few operators choose to grow crops in Union County due to marginal soils and less reliable groundwater resources (Wenger 2015; Zeigler 2011). Despite this, CPI installations have also increased dramatically since installations began in the 1970s, covering over 50,000 acres in 2014 (Wenger, Vadjunec, and Fagin 2017, 10).

Flora and Fauna

Vegetation in the study area is composed primarily of shortgrass prairie, with areas of juniper woodlands and shrublands interspersed particularly in areas of greater relief (Fagin et al. 2016). The two counties represent areas of unique vegetation relative to their respective states, though unfortunately are largely understudied (Hoagland 2000; NPS 2004). Cimarron County has been called a "distinct biotic district" in Oklahoma (Blair and Hubbell 1938), boasting *Juniperus monosperma* woodlands, rare stands of *Pinus ponderosa*, highly diverse playa lakes (Hoagland 2000), and over 23 rare plants at Black Mesa alone (The Nature Conservancy 2019). Unique plant communities in Union County vary by elevation and include juniper-oak and pinyon pine woodlands (NPS 2004), stands of *Pseudotsuga menziesii* (Douglas fir), and *Pinus ponderosa* (ponderosa pine) (Guyette 2006).

Cimarron County is home to 852 documented plant species (Oklahoma Vascular Plants Database 2019), while 583 plant species have been documented in Union County (New Mexico Biodiversity Collections Consortium 2019). Grasslands in the region are comprised most commonly of *Buchloe dactyloides* (buffalograss) and *Bouteloua gracilis* (blue grama). In addition, *Bouteloua curtipendula* (sideoats grama), *Schizachyrium scoparium* (little bluestem), and *Boutela hirsuta* (hairy grama) are observed in sandier, wetter areas (Tyrl et al. 2007). Drier localities may contain grasses including *Pascopyrum smithii* (western wheatgrass), *Stipa comata* (needle-and-thread), and *Sporobolus cryptandrus* (sand dropseed) (Hazlett 2009).

A number of additional herbaceous species are commonly observed in grasslands including thistle, milkweed, slender scurpea, and a variety of additional forbs (Castetter 1956). Sandsage grasslands are common in sandy soil in the northern reaches of the study area, and feature mixed communities of *Artemisia filifolia* (sandsage), *Rhus aromatica* (fragrant sumac), and *Yucca glauca* (plains yucca) (Tyrl et al. 2007). Sandy areas are also home to a variety of shrubs, half-shrubs, and cacti including *Gutierrezia spp*. (broom snakeweed) *Chrysothamnus spp.* (rabbit brush), *Cylindropuntia imbricata* (walking stick cholla), *Prosopis glandulosa* (mesquite), and *Opuntia phaeacantha* (New Mexico prickly pear) (Castetter 1956). While these species are native to the study area, past research has indicated their abundance has increased in recent decades.

Grasslands in the study area support a variety of fauna, which play a crucial role in herbivory and nutrient cycling (Ford and McPherson 1996). Among the major herbivores are pronghorn antelope, mule deer, bighorn sheep and elk (Clark 1968a, 1968b; The Nature Conservancy 2019). A variety of additional megafauna have been observed including black bear, coyote, mountain lion, swift fox, and bobcat (Hazlett 2009). Although the region has relatively low small mammal diversity, black-tailed prairie dog is present and plays a major role in nutrient cycling in soils (Clark 1968a). Biodiversity is high, however, for arthropods, with over 25 species of grasshoppers in the region and diverse assemblages of ants, spiders, and beetles (Ford and McPherson 1996). Additionally, grasslands in the study area serve as important habitat for hundreds of bird species, including spotted towhee, Ferruginous hawk, long-billed curlew, burrowing owl, and mountain plover (Hazlett 2009; Johnson et al. 2003). An increase in woody vegetation in the area, however, threatens to reduce this available habitat (Johnson et al. 2003).

WPE in Union and Cimarron Counties

Ground-based vegetation observations in the area have indicated that the extent and abundance of woody species such as *Juniperus monosperma* are increasing (Johnson et al. 2003; NPS 2004). However, previous research has been limited mostly to local scales, though one study utilized satellite-based remote sensing to examine vegetation change in the region. Fagin et al. (2016) used a temporal analysis of the National Land Cover Dataset (NLCD) to examine the extent of WPE on public and private lands in the same bi-county study area. Between 1992 and 2011, Cimarron County's total area experienced a 631% increase in shrubland, while Union County saw a 104% increase. Herbaceous land-cover remained the dominant category, covering nearly 76% of the study area (Fagin et al. 2016, 7). However, the increase in woody vegetation, which was most severe in the northern portions of the study area along the Dry Cimarron River, raises questions regarding the long-term sustainability of cattle ranching in the region. WPE was most severe in Cimarron County's state leased lands, and least severe on federal lease lands, implying that land tenure and governance may result in differential land management practices. As Vadjunec and Sheehan (2010) note, open bidding policies and short lease terms on state lands may result in a lack of incentives for lessees to consider the long-term implications of their land management decisions.

CHAPTER II

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

As plant communities in rangelands of Cimarron County and Union County are altered, a number of interrelated knock-on effects have emerged. Specifically, biophysical feedbacks involving soil erosion and loss of biodiversity can accelerate land degradation, which then trigger additional feedback cycles affecting land management decisions (Claessens et al. 2009). Acknowledging the complexity of WPE and its associated effects, this thesis uses a land system science (LSS) approach to untangling the people, patterns, and processes of land degradation (Frazier, Vadjunec, et al. 2019). In the sections that follow, a general overview of the field of LSS is provided, followed by specific examples of LSS applications in land degradation, landowner decision-making, and remote sensing. Additionally, a description of biodiversity is presented, followed by a brief discussion of the issue of scale in LSS and remote sensing.

Land System Science and its Antecedents

While all organisms modify their environment, the influence of human land-use through mechanisms such as agriculture, construction, and manufacturing has yielded dramatic effects on earth's biotic and abiotic landscape (Schlesinger et al. 1990; Turner and Gardner 2015; Zube 1987). Human modifications to land have contributed to mass extinctions (Ceballos, Ehrlich, and Dirzo 2017; Stuart and Peter 2000; Wake and Vredenburg 2008), climate change (Parmesan and Yohe 2003), loss of ecosystem services and productivity (Dube and Pickup 2001), and reduction in available freshwater (Carpenter et al. 1992), among many other effects. Notably, the synergistic relationships of these factors tend to produce feedback cycles which further intensify their effects (Geist and Lambin 2004). Further, interactions between anthropogenic change and natural environmental variation also add complexity to these systems (Ravi et al. 2010).

As human modifications to earth continue to expand and intensify, investigations into the effects of the Anthropocene—the current geologic period in which humans are the most significant drivers of change—have also been intensified (Zalasiewicz et al. 2010). While remote sensing has long been used to measure these modifications (Lambin and Strahler 1994), a number of theoretical foundations for such research have been proposed (Wu 2019), including land-use/land-cover change (LULCC) and Land System Science (LSS).

LULCC emerged in the 1980s as an interdisciplinary approach examining both changes in the biophysical characteristics of the landscape, as well as the anthropogenic drivers of these changes (Meyer and Turner 1992). By the mid-1990s, the International Geosphere-Biosphere Programme (IGBP) and Human Dimensions of Global Environmental Change Programme (HDP) formalized an international joint research plan to study global environmental change (Turner et al. 1995). Acknowledging a need to more fully understand the causes and extent of LULCC, (Turner et al. 1995, 20), the research agenda prioritized three major foci: (1) case studies of land-use dynamics, (2) remote sensing and field studies of land-cover dynamics, and (3) modeling of regional and global change (Brannstrom and Vadjunec 2014, 4).

However, as LULCC matured and evolved, geographers saw the need for a more nuanced "systems" framework (Turner et al. 2013; Verburg et al. 2013). For example, the Global Land Project proposed as a more holistic approach examining the “people, biota, and natural resources (air, water, plants, animals, and soil)” associated with the land (GLP 2012, 1). The approach to LULCC, continued to evolve, since the landscape and its associated processes and feedbacks evolve over time (Aspinall and Hill 2007). As a result, over the past 25 years, LSS has grown in tandem with LULCC studies (Rounsevell et al. 2012).

LSS implements a dynamic, integrative approach to answering questions of global environmental change, going beyond measuring LULCC by also examining “how human actions affect natural processes” and evaluating “the consequences of these changes” (GLP 2005, 1), often examining land management decisions (Turner, Lambin, and Reenberg 2007; Moran, Skole, and Turner 2004), socio-economic factors (Ellis and Ramankutty 2008), and the feedbacks between the two (Turner et al. 2013). In these feedback cycles, land management decisions are influenced by the existing land characteristics, which then further act to alter the land, and vice versa (Verburg et al. 2013). These interrelated factors and feedbacks demonstrate the complexity of human-environment systems. As Liu et al. (2007, 1513) explains, human-environment systems are not simple balance sheets of ecosystem inputs and outputs, but “they also exhibit nonlinear dynamics with thresholds, reciprocal feedback loops, time lags, resilience, heterogeneity, and surprises." Further, LSS interrogates not only *how* the land is changed, but also *why* landowners make decisions to change it (Hecht 1993).

In terms of methodology, this approach often involves modeling of the economic, environmental, political, or social factors involved in decision-making and subsequent land-use/land-cover changes as a means of systematically explaining the complex interactions of these factors (Rounsevell et al. 2012; Lambin and Meyfroidt 2010; Rindfuss, Walsh, Turner, et al. 2004). Further, consistent with its antecedents, remote sensing and/or field observations are often implemented to measure land degradation (Wu 2019). This considered, detecting land degradation is often not a simple task, but is complicated by the subjective ways in which it may be defined.

<u>Land Degradation in LSS</u>

While definitions of land degradation vary, most focus on a decrease in biodiversity or biomass, typically in response to human modification. For example, Johnson and Lawrence (2007, 2) presents two critical criteria for identifying a decline in land condition: "First, there must be a substantial decrease in the biological productivity of a land system, and second, this decrease is the result of processes resulting from human activities rather than natural events." Similarly, Blaikie and Brookfield (1987) emphasize a decrease in productivity, with a focus on the resultant "cost" to labor. In this sense, land degradation impacts not just the land itself, but also its biota including livestock and vegetation, its water systems that support these organisms, and the humans that rely on the entire system.

Others argue that no single definition can exist for land degradation since different stakeholders may have subjective opinions (Warren 2002). Blaikie and Brookfield (1987, 4-5), for example, define degradation as a "reduction to a lower rank," while acknowledging that rank is a "scale of relative measurement" established by various land users with different perceptions of what constitutes value or proper use. For example, biophysical scientists examining nutrients and species composition may draw different conclusions about land quality than economists simply measuring land potential (IPCC 2019). Further, landowners may have entirely different environmental perceptions, especially in cases where cultural differences and even land-use priorities cause different parties to disagree on current land conditions (Bürgi, Li, and Kizos 2015).

Additionally, while some stakeholders may focus on short-term gains, others prioritize long-term sustainability (Shiferaw and Holden 2001), such as in issues of afforestation (Schneider et al. 2001). Further, while many traditional definitions of land degradation describe *decreases* in biological productivity, an *increase* in vegetation could also be cited as an example of degradation, such as when invasive species emerge and outcompete native vegetation (Turner, Lambin, and Reenberg 2007). Three types of land degradation relevant to this thesis—soil erosion, overgrazing, and desertification—are detailed below.

Soil Erosion

Many prominent examples of land degradation involve soil erosion (Blaikie 1985; Pickup, Bastin, and Chewings 1998), often with agriculture as the primary cause. At least 1/3 of topsoil on U.S. cropland has been eroded over the past two centuries (Pimentel et al. 1976), decreasing agricultural potential and increasing sediment loads that may harm water resources (Geist and Lambin 2004; Pimentel et al. 1976). The Dust Bowl of the 1930s is perhaps the most well-known example of widespread soil erosion. In this example, key indicators of land degradation are clearly present: vegetative cover on cultivated lands was significantly reduced through tillage (Lee and Gill 2015), resulting in further disturbance to agriculture.

An LSS perspective is especially relevant to this case because of the complex feedback cycles emerging both from new land-use processes and unique environmental conditions. To this point, some have argued that the Dust Bowl was not just a consequence of problematic agricultural practices, but was also an outcome of expanding agriculture into a semi-arid region (Reisner 1986). According to Johnson (2007, 10) "it represents the prototype example of ecological failure resulting from drought in areas where rainfed agriculture has been extended beyond the limits of humid areas." To illustrate this, Cook, Miller, and Seager (2009) constructed a model showing that both land use and environmental factors (anomalous sea surface temperature and drought) worked in tandem to create the Dust Bowl. Therefore, while land degradation by definition is associated with human modification of lands, feedback cycles can emerge in which climate amplifies the effects of anthropogenic degradation. Further, though crop cultivation has become widespread, grazing also can result in degradation of land.

Overgrazing

Managed grazing occupies roughly one-quarter of the global land surface, covering more area than any other land use (Asner et al. 2004). While responsible grazing can have positive benefits in some systems (Bakker 1985), overgrazing can cause bare soil patches and increase susceptibility to erosion or invasion by non-native species (Oldeman 1992). Overgrazing has been observed on a global scale, but began in rangelands of the United States around 1875 (Dube and Pickup 2001; Pickup, Bastin, and Chewings 1998), causing a variety of ecological issues and threats to agricultural sustainability with profound consequences for the global food supply (Wilcox and Huang 2010).

As a prominent integrative case study in grazing effects, Schlesinger et al. (1990) observed a delicate balance wherein native black grama grasses rely on specific patterns of precipitation and soil moisture which dictate seasonal photosynthesis and the development of shallow root structures. However, the introduction of livestock disrupts sensitive soil moisture and nutrient profiles through removal of vegetative cover, trampling, and compaction. Grasses then become degraded through increased heterogeneity of nutrients (most importantly, N and C), moisture, and soil density (Manley et al. 1997; Schuman et al. 1999). Subsequently, feedbacks with soil erosion processes may occur (Schlesinger and Jones 1984), which can increase albedo and promote desertification of grasslands (Gong Li et al. 2000).

Desertification

Closely linked with grassland degradation is desertification, wherein both anthropogenic modifications and climate variability cause further desiccation of drylands. According to Geist and Lambin (2004, 817), "there is a great deal of debate […] on the degree to which these causes are local or remote, and on how variables interact across organizational levels in different regions of the world and at different time periods”. Although these dynamic interactions differ from the solely human-caused criteria of degradation presented by Johnson and Lawrence (2007), desertification is certainly emblematic of an overall reduction in biological productivity and agricultural potential (Dregne 1977).

Consistent with LSS feedbacks, desertification involves a reduction in vegetative cover, accompanied by increasing soil surface and air temperatures, and consequent reductions in relative humidity, cloud production, and precipitation (Otterman 1974; Taylor et al. 2002). Balling (1988) observed this effect in the Sonoran Desert, where fencing between Mexico and the United States delineated zones of dramatically different grazing practices. Overgrazing on the Mexico side resulted in shorter grasses and increased bare soil, causing a warmer, drier regional climate compared to that of the intact grasslands on the north side of the border. Of course, this effect was in part a result of landowner decision-making regarding grazing intensity, which itself is complex and influenced by a variety of factors.

Landowner decision-making

In coupled human and natural systems, exposure to environmental hazards and stressors can cause humans to react in a variety of ways (Munroe et al. 2019; Roche et al. 2015). Lambin and Meyfroidt (2010) proposed a dualistic system of forces that influence land-use decisions: (1) endogenous socio-ecological feedbacks, and (2) exogenous socio-economic changes. In the former category, landowners consider the availability of natural resources when making decisions (e.g., “Do I have enough grass for my cattle?” or

"When will the next rain come?"). In the latter category, decisions are affected by market forces, policy prescriptions, and technological innovation (e.g., "Should I wait to sell my cattle until prices increase?" or "Is it cheaper to buy feed or lease more land?"). Land tenure, cost, and availability are also important exogenous factors (Vadjunec and Sheehan 2010; Dube and Pickup 2001).

Often, endogenous and exogenous factors work in tandem. For example, Vassilis, Helen, and Constantinos (2017) found that landowners in Greece often chose to intensify grazing despite land degradation (endogenous) due to of a lack of economic alternatives (exogenous). As a result, long-term consequences can arise from short-term situations. Therefore, landowners, policy makers, and academics may disagree about best practices, since decision-making is subjective in the same manner as degradation itself (Warren 2002). The feedbacks of these decisions, however, are well documented, where land degradation frequently results in intensification of grazing, which further reduces land potential (Liu et al. 2007; Otterman 1974; Taylor et al. 2002) and may result in increased vulnerability for those using the land.

Vulnerability and Resilience in Grasslands

Ultimately, land-use decisions may act to increase vulnerability (e.g., overgrazing which can produce feedbacks that further degrade land) or increase resilience (e.g., decreasing cattle stocking rates to benefit land but suffer economically in the short-term) (Turner et al. 2003). However, there is little consensus on specifically which biophysical traits constitute resilience in grasslands. Johnson and Lawrence (2007, 9) defines resilience as the ability of the land to "absorb change without significantly altering the relationship between the relative importance and numbers of individual species that compose the community" (see also Folke 2006; Walker et al. 2004).

Grasslands have been observed to recover from degradation, particularly after significant precipitation events (Cowling, Richardson, and Pierce 1997). However, Dube and Pickup (2001) argue that the potential for recovery becomes decreased as stocking intensity and extent increases, since N turnover is reduced with further agricultural intensification (Schlesinger et al. 1990) and invasive species may outcompete native vegetation (Alofs and Fowler 2013). Additionally, attempts to improve land in the short-term through the use of fertilizers, herbicides, or pesticides may be counterproductive by reducing soil biota and available carbon (Matson et al. 1997). As Reynolds et al. (2007) note, the cost of intervention in these scenarios increases non-linearly with additional degradation. One strong indicator of a grassland's recovery potential, however, is its biodiversity, or the assemblage of species present (Vogel, Scherer-Lorenzen, and Weigelt 2012)

Biodiversity

A loss of biological diversity is a common consequence of land-use change and degradation (Jenkins 2003). Biodiversity may be defined in a variety of ways, but at its most basic refers to the assemblage of various species that occupy an ecosystem (Gregorius 2016). Measurement of biodiversity may involve a number of metrics, ranging from simple species richness (the number of unique species), to more complex analyses of the distribution, relative abundance, and phylogenetic diversity of species (Magurran 1988; Schulze et al. 2004; Walker 1992). Assessments of biodiversity change can also take many forms, including four main types: "species extinctions, species abundance and community structure, habitat loss and degradation, and shifts in the distribution of species and biomes" (Pereira et al. 2010, 1496). Biodiversity can also be subjective, as explained by Mapinduzi et al. (2003) who observed that indigenous systems of rangeland assessments and indicator species implemented by Maasai pastoralists helped to determine grazing suitability and preserve communities of native species long-term.

Ecologists have proposed that greater biodiversity confers increased ecosystem stability by strengthening interspecies interactions and filling a variety of ecological niches (Pennekamp et al. 2018), potentially increasing resilience to environmental hazards such as drought or floods (Naeem 2002; Zavaleta and Hulvey 2004). Isbell and Wilsey (2011), for example, found that increased species richness in grasslands improves resilience to grazing by increasing aboveground productivity and reducing degradation of fine root biomass. Additionally, biodiversity may provide temporal stability, since many systems experience successions of species over time or may be expanded or reduced seasonally (Cardinale et al. 2012; Zemunik et al. 2016). Conversely, a decrease in biodiversity has been associated with decreased ecosystem function (Srivastava and Vellend 2005). Unfortunately, in the midst of the Anthropocene and earth's sixth mass extinction, biodiversity has rapidly decreased, particularly in the last 50 years (Metzger et al. 2006), with over half of all species experiencing anthropogenic impacts (Ceballos, Ehrlich, and Dirzo 2017; Meyers et al. 2000). As a result, a small number of generalist species have in many cases expanded to take over habitat previously occupied by a rich diversity of species (McKinney and Lockwood 1999). Considering this apparent global anthropogenic land degradation, measurements of biodiversity can be immensely useful in LSS studies.

Biodiversity in LSS

Despite the increasing similarities between landscape ecology and LSS (Roy Chowdhury and Turner 2019) and the imminent global threats to biodiversity (Dinerstein et al. 2019), few studies have integrated biodiversity in land systems research (Frazier, Bryan, et al. 2019). Because biodiversity provides critical ecosystem functions (Schwartz et al. 2000), effective LSS investigations could move beyond simply making remote sensing observations by directly measuring ecosystem functions such as soil fertility, erosion control, habitat for wildlife, crop pollination, and agricultural production, among others (Martínez et al. 2009; Olschewski et al. 2006; Zavaleta and Hulvey 2004). Additionally, landowner decision making often plays a direct role in biodiversity; short-term economic gains achieved through reductions in biodiversity (e.g., through monocropping or deforestation) present quandaries when they later reduce agricultural productivity (Corbera, Estrada, and Brown 2010; Siewe, Vadjunec, and Caniglia 2017).

Scale in Biodiversity

Just as the method of measuring biodiversity can influence the results of an investigation, so too can the scale of measurement. As Seppelt, Lautenbach, and Volk (2013, 1) note, "any global analysis benefits from systematic synthesis of sub-global research from various scales, while sub-global investigations require embedding in global scenarios." Because human activities are the most direct drivers of biodiversity loss, local scale observations lend themselves to associations with individual land-use practices (Newbold et al. 2015; Schulze et al. 2004). To elaborate, strictly local investigations in biodiversity may fail to acknowledge feedbacks at broader scales such as climate or exogenous political and economic forces. Conversely, global scale observations may not always scale down to local observations, which typically exhibit greater variation in biodiversity (Bennett et al. 2015). Further, links between biodiversity and ecosystem services are often identified at local and regional scales, but may be obscured at broader scales (Turner et al. 2007).

A similar pattern has been observed in examining the relationship between biodiversity and resilience to invasive species at varying scales (Alofs and Fowler 2013; Zavaleta and Hulvey 2004). The so-called "invasion paradox" claims that fine-scale studies often associate loss of biodiversity with increased invasion vulnerability, since fewer species are present to outcompete non-native ones. However, at larger scales, ecosystems with high species richness facilitate more invasive species because generalists can readily adapt to the favorable climate or resources that had initially resulted in the abundance of species (Levine 2000). Numerous reports have examined these trans-scalar effects, however few have acknowledged the subjectivity of biodiversity, particularly with regard to short-term decision-making by landowners.

While the theoretical foundations of scale in biodiversity have been thoroughly discussed, assessment of biodiversity in the field presents a number of practical considerations that may complicate assessments. Surveys and sampling efforts may require considerable time or financial resources, depending on the assessment techniques involved (Archaux et al. 2006; Stohlgren, Bull, and Otsuki 1998). As Kent and Coker

(2011) explain, the choice of sampling methods typically depends on the purpose and scale of the study; the increase in time and cost associated with surveys becomes amplified as the spatiotemporal extent of the investigation increases. Rapid assessment techniques have emerged in response to these concerns, with some researchers proposing that use of indicator species (Oliver and Beattie 1993) or extrapolated species counts (Oliver and Beattie 1996) may reduce required time and effort with only a minor impact on data quality.

Another approach, commonly used in vegetation assessments involves a hierarchy of multiple scales, because, as Noss (1990, 357) puts it, “big questions require answers from several scales.” A common method proposed by Peet, Wentworth, and White (1998), and implemented in the International Forestry Resources and Institutions (IFRI) Research Program (Wertime et al. 2007), involves a system of nested plots at multiple scales. Through this method, all species are recorded within a small area, while certain other species (typically shrubs are trees) are recorded in larger scale plots. Through this approach, the theoretical foundation proposed by Montello (2001) is satisfied, in which the scale of analysis reflects the scale of the phenomena (i.e., the size of various species) being observed. By the same token, nested plots utilize scale that reflects the variation in patterns and distribution across the landscape, as recommended by Moellering and Tobler (1972).

Although nested biodiversity plots can resolve scalar issues in some instances, the time and resources required for ground-based observations limit their spatial extent (Wiens 1989). As a result, remote sensing is frequently implemented at regional and global scales as a means of collecting data across broader spatial extents with reduced time and financial resources (Franklin 2010).

Remote Sensing

Use of remote sensing techniques, such as classification of satellite or aerial imagery has long been a crucial component to investigations in LULCC (see Hansen and Loveland 2012; Hansen et al. 2013; Wulder et al. 2008; Zhan et al. 2002), with integrated remote sensing/social science research appearing by the early 1970s (Estes, Jensen, and Simonett 1980). Acknowledging that land-use change and its underlying socioeconomic drivers are deeply interwoven, a movement emerged to more purposefully link “people to pixels” (Wood and Skole 1998), particularly in cases of agricultural expansion, deforestation, or land degradation (Roy Chowdhury and Turner 2019). As Rindfuss and Stern (1998, 6) note, “remote sensing can provide measures for a number of dependent variables associated with human activity—particularly regarding the environmental consequences of various social, economic, and demographic processes.” Such investigations often implement remote sensing as an “objective” measure of change, coupled with household surveys to interrogate the underlying reasons for change.

This fusion of data sources has been demonstrated in numerous case studies ranging from fires in Indonesia (Dennis et al. 2005) and drought effects on pastoralists in east Africa (Galvin et al. 2001) to loss of grass and savannah woodlands in Ghana (Yiran, Kusimi, and Kufogbe 2012) and rubber tapper activities in the Brazilian Amazon (Vadjunec 2007). Notably, findings from these different data streams may yield contradictory results. For example, Herrmann, Sall, and Sy (2014) used satellite imagery to identify areas of re-greening in the Sahel, as well as focus groups, key informants, and participatory mapping exercises to help identify local perceptions of re-greening. However, areas of degradation and re-greening differed between remote sensing and social science methods, indicating that different aspects of degradation may be relevant to different groups, as proposed by Warren (2002). In mixed methods approaches, others have incorporated additional information such as ground-level observations or census data to further triangulate patterns and causes of land change (e.g., Galvin et al. 2001; Homer et al. 2012; Wood and Skole 1998), acknowledging that phenomena such as biodiversity can be difficult to capture through remote sensing. Further, bridging household-level observations with biodiversity or remote sensing data at different scales can present additional challenges.

Issues of Scale in LSS

Just as scale of analysis can influence biodiversity and remote sensing, investigations in LSS more broadly can be biased by scale. Because LSS often implements mixed methods to examine local-scale processes through household surveys and regional/global-scale processes through remote sensing (Liverman and Cuesta 2008), contradictory findings may arise (Warren 2002). For this reason, landscape-level investigations have been crucial in helping to connect local land use with broader scale change (Wu 2011). Such "intermediate-scale" studies benefit from using the landscape as a focal unit of analysis, while also directly considering processes at other scales (Kates 2012; Wu 2019).

Research that ignores meso-scale observations may face challenges in linking processes at vastly different scales (Wiens 1989). Issues can arise in linking "people to pixels" because land ownership changes periodically or because pixel resolution may be insufficient to rectify against parcel resolution (Rindfuss, Walsh, Turner, et al. 2004, 13977). Additionally, the phenomenon of the ecological fallacy states that evidence collected at one scale cannot reliably yield conclusions about a different scale (Harris 2006). Further, it must be noted that the driving forces of land change operate at multiple scales. While individual plot-based decision-making occurs at a microscale (Blaikie 1985), regional scale processes such as climatic factors (Geist and Lambin 2004) and governance (Buizer, Arts, and Kok 2011) can each alter land systems but be detected only at certain scales. Thus, integrating multiple scales of analysis can help to clarify scalar limitations and provide a more holistic picture connecting process to patterns (Li et al. 2017).

Additionally, while spatial scale clearly matters, the relevance of temporal scale should not be understated. As Dearing et al. (2010) note, long-term analyses of land systems help to clarify whether degradation has occurred as part of natural processes, or if anthropogenic factors have played a more significant role in the recent term. This issue intersects with methodological approaches, where the temporal scale of remote sensing data, for example, might affect conclusions (Rindfuss, Walsh, Turner, et al. 2004).

Effects of Remote Sensing Resolution

As with LSS more broadly, the issue of scale in remote sensing may dramatically influence findings, with different resolutions each exhibiting varying benefits and tradeoffs. Remote sensing analyses of vegetation change using satellite imagery have become more prevalent in recent years (Starks et al. 2011; Wang et al. 2018; Fagin et al. 2016), with the obvious advantages that data may be collected quickly with little effort compared to ground-level assessments, and multiple time series may be analyzed as frequently as new imagery is captured. However, the spatial resolution of satellite imagery may not meet the needs of some research questions. For example, in forestry studies, fine-resolution imagery has been implemented to identify individual trees, while coarser resolution imagery can help provide data related to forest density or the occurrence of large stands of trees (Woodcock and Strahler 1987). Nested/hierarchical approaches to scale have also been advocated in remote sensing because of the advantages of examining data at multiple scales. Goodchild (2011) highlights the tradeoffs between various scales, wherein coarser-scale data often confers broader spatial extents, while fine-scale data typically provides greater detail within a smaller area. This observation was corroborated by Homer et al. (2012), who used three different scales of satellite imagery to detect degradation of sagebrush ecosystems in Wyoming, finding that the highest resolution imagery conferred the greatest classification accuracy.

In bridging the gap between scales, a novel approach might involve examining the same system from multiple perspectives, including satellite imagery, ground-level vegetation sampling, and a social science (or household) component to help describe the land-use behaviors underlying land change. For example, Vadjunec and Rocheleau (2009) implemented this approach to describe deforestation patterns in the Chico Mendes Extractive Reserve in Brazil. The authors used Landsat imagery to quantify overall forest cover change, plot-level vegetation sampling to measure loss of biodiversity, and household surveys to understand resource extraction processes. Although this type of multi-scale investigation certainly provides an important level of detail and nuance in LSS (Liverman and Cuesta 2008; Dennis et al. 2005), it remains uncommon. Perhaps one reason is the significant time and resources required to complete such an exhaustive study; Vadjunec and Rocheleau (2009) implemented rapid vegetation appraisals to improve efficiency, but now, a decade later, the topic of rapid assessment in multi-scale LSS investigations is due for reexamination.

Unmanned aerial systems (UAS) have emerged as a promising candidate for increasing the efficiency and accuracy of rapid assessments, as they have been used in a variety of applications including rapid assessment of disaster damage (Restas 2015), fire (Laszlo, Agoston, and Xu 2018), wildlife surveys (Brack, Kindel, and Oliveira 2018; Christie et al. 2016; Watts et al. 2010), and vegetation (Husson, Reese, and Ecke 2017; Visser, Wallis, and Sinnott 2013; Zweig et al. 2015). Despite its potential, UAS imagery has been mostly confined to geophysical investigations, very few studies directly linking UAS to anthropogenic effects and social science (though see Paneque-Gálvez et al. 2017; Cummings et al. 2017). The utility of fine-scale remote sensing serves to better inform LSS investigations by providing data both on larger-scale patterns, while also improving detail of vegetation analyses beyond those capable with satellite imagery. Further, while a theoretical foundation exists regarding the scalar difference between satellite and UAS remote sensing, few investigations have assessed these differences empirically.

Summary

Through an LSS framework, the interconnectedness and relevance of land degradation, climatic interactions, landowner decision-making, biodiversity, and the methodology/scale by which each is investigated becomes critically important to triangulating the causes and effects of landscape change. Central to this approach is the identification of feedback cycles and processes in which components affect and potentially amplify one another. In this investigation specifically, the interrogation of synergistic biophysical and land management factors helps to more clearly elucidate the causes and patterns of woody plant encroachment in Union and Cimarron Counties. Additionally, through examining the biodiversity component of WPE and herbaceous species in this system, this thesis explores how species richness may confer resilience to natural hazards, how landowner practices affect biodiversity, and what ecosystem services may be provided as a result of diverse community assemblages. While past research has used a variety of methods to examine these interrelated processes, this investigation serves as a novel implementation of UAS imagery as a bridge in scale and rapid assessment tool which may help to improve the quality and detail of data collected without sacrificing efficiency. In the following chapters, these methods are explained in detail, followed by a discussion of the research outcomes and its implications for LSS more broadly.

CHAPTER III

METHODOLOGIES

Implementing an LSS approach, and collecting data from a range of sources and at a variety of scales, this investigation seeks to identify the complex and interconnected forces affecting each of the three research questions stated in Chapter 1. As this chapter continues, methodologies are presented in order from the smallest scale of analysis to the largest. This structure is also paralleled in Chapter 4. At the finest scale, household surveys with landowners and land managers provide a foundation upon which all other analyses are based. Next, ground-level vegetation sampling in nested plots on the survey respondents' property provides ground-truthed data used in biodiversity calculations. Next, UAS imagery provides a meso-scale perspective useful for quantifying herbaceous cover, woody plants, and bare soil. Additionally, Structure from Motion Multi-View Stereo (SfM-MVS)-derived data provided through UAS remote sensing allows fine-scale detection of vegetation heights to aid in species-level classification. Finally, satellite remote sensing in the form of the National Land Cover Dataset (NLCD) provides a coarser but broader perspective on the entire region. Integrating climatic, terrain, and soils data with the NLCD through multiple regression then further elucidates the role of environmental factors in woody plant encroachment (WPE).

The synthesis of these varied methods ultimately informs the three research questions through bridging multiple spatial scales and methodologies, as described in Table 1.

Table 1: Methods and Synthesis of Research Questions

	Question 1 *How does woody plant encroachment vary across different environmental gradients, land-use/management practices, and sociopolitical boundaries?*	**Question 2** *What is the relationship between herbaceous plant biodiversity and woody plant encroachment? How does it vary across scales?*	**Question 3** *What are the benefits and limitations of multiple scales of analysis, particularly considering the potential role of unmanned aerial systems (UAS) as a scalar bridge in rapid vegetation assessments?*
Methods	• Household Surveys • UAS Imagery • NLCD Modeling	• Ground-Level Vegetation Assessments • UAS Imagery	• Ground-Level Vegetation Assessments • UAS Imagery • NLCD Modeling
Synthesis	• T-tests comparing observations between different land use/management types • Linear regression comparing ground-level biophysical observations with biodiversity and UAS-derived land cover • T-tests and Chi square tests evaluating differences between counties	• Linear regression and paired t-tests comparing metrics obtained through ground- and UAS-based observations • Correlation matrix comparing different levels of measurement	• Linear regression, paired t-tests, and ANOVA comparing results of different scales

As this chapter continues, a detailed description of how each dataset was acquired and was analyzed is presented, followed by further discussion of how these datasets were synthesized and compared to address each research question.

Household Surveys

In alignment with common LSS practices, this investigation uses household surveys as a means of leveraging local knowledge and perspectives to provide context (Rindfuss, Walsh, Mishra, et al. 2004). As part of a larger USDA-funded project called *ARID* (Ganguli et al. 2018), survey participants *(n=20,* a subset of the project's 135 total) were recruited during the summer of 2018 through community meetings, local events such as senior and community lunches, fishing derbies and county fairs, key informant interviews, already existing research in the region, and/or names garnered from county plats and/or USDA agricultural subsidy records (EWG 2018). This research expands on the knowledge garnered from previous household surveys completed in the study area (Vadjunec et al. 2013). All human subjects research was conducted under approval from the Oklahoma State University Institutional Review Board, application number AS-18-24 (Appendix I).

Household surveys were conducted in May and June 2018, primarily in participants' homes (n=20, 10 in each county), and typically lasted 1.5-3 hours. Surveys were typically followed by planning of vegetation sampling and UAS flights on the participants' property. The household survey asked participants to rate how they perceive the severity of various species on their land on a scale from 1 through 5 (with higher numbers indicating greater severity). Lists of species were generated from previous research in the area (Colston, Vadjunec, and Fagin 2019; Fagin et al. 2016), though respondents were encouraged to add any species they perceived as a "nuisance."

Additionally, participants provided details regarding efforts for prevention and removal of problematic species at two scales: (1) efforts made in general across their entire landholdings (Appendix II), and (2) land history and management actions over the past ten years related specifically to plots where vegetation sampling and UAS photography were conducted (Appendix III). Relevant land management actions were sourced from the literature (Van Auken 2009) and extension specialists in the area, and included the use of prescribed fire, mowing, manual removal of vegetation (e.g., chaining, use of backhoe, etc.), herbicide applications, or any other actions deemed relevant by respondents. Respondents also detailed grazing intensity or participation in the Conservation Reserve Program (CRP) for the vegetation sampling/UAS plots. Examining land use and history at two scales helps to provide both a broad-picture overview of landowner awareness and actions related to nuisance plants as well as detailed plot-level data that can be associated directly to broader-level sampling and remote sensing.

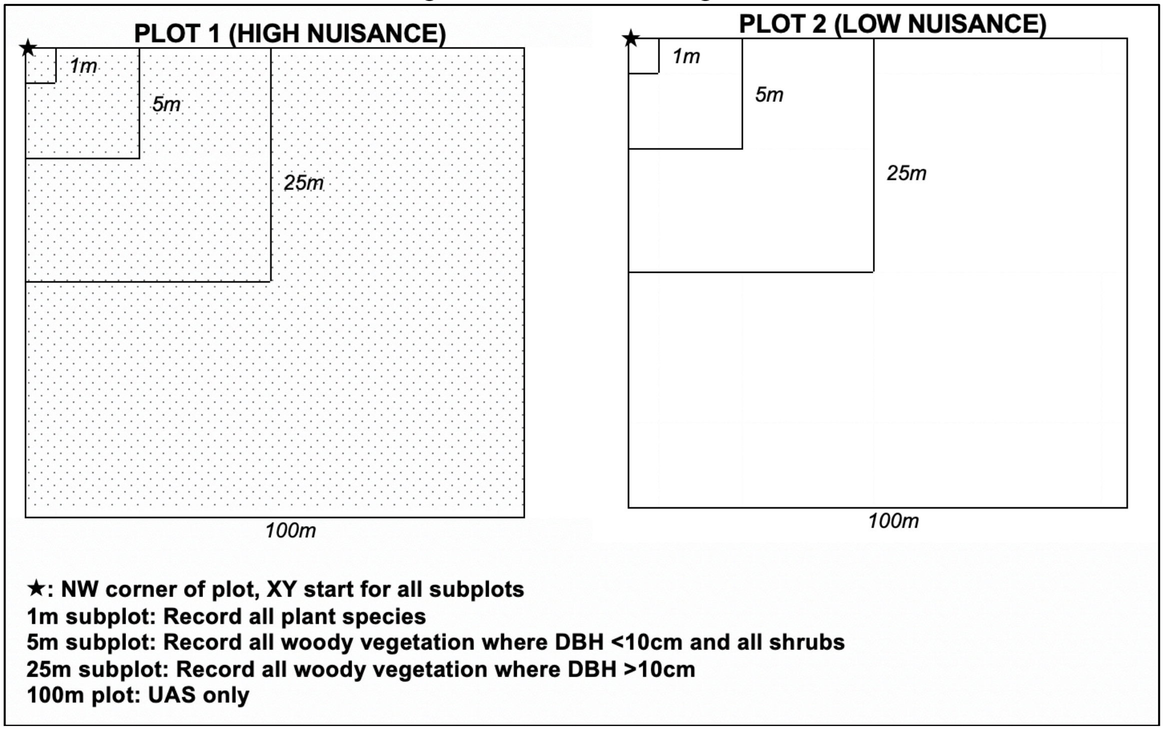
Upon completion of household surveys, a codebook was generated to ensure consistent database entry of survey forms. A Microsoft Excel file was created with fields representing each survey question, including both quantitative responses such as acreage or Likert scale responses, as well as qualitative responses to open-ended questions. The spreadsheet was then populated with responses from the 135 respondents according to codebook specifications. Data was then queried to obtain proportions of respondents sharing common perceptions and land-use practices. Frequency plots for Likert scale questions were produced using Microsoft Excel. Where appropriate, data was pooled at multiple scales of analysis, including county-level and by landowner perception (intact or encroached plots). Significant differences between groups were analyzed using two-tailed t-tests in Microsoft Excel and the software package R.

Ground-Level Vegetation Sampling, Rangeland Health, and Biodiversity

As a means of assessing ground-level data related to vegetation and environmental characteristics, rapid assessment measures of species presence, rangeland health metrics, and soil traits were collected on each survey respondent's property. Following each household survey, respondents were asked to select two rangeland plots of roughly 12 acres each, in which one had perceived issues with invasive or nuisance species (hereafter referred to as “encroached”), and another which had fewer or no issues with problematic vegetation (“intact”). In preserving the integrity of participatory methods and the subjectivity of land degradation, landowners were asked to select their plots based on any species of personal concern, which ranged from woody plants such as juniper, yucca, and cholla, to other problematic rangeland issues such as locoweed, which produces phytotoxins harmful to livestock, and prairie dogs, which create borrows that can injure cattle. Once the plots were selected, participants drew a planned flight area on printed satellite imagery maps. In some cases where participants were more comfortable using technology, researchers and participants worked together to configure a flight plan using the DroneDeploy app for iPad.

Using methods adapted from the International Forestry Resources and Institutions sampling protocol (Ostrom 1999), one 1 square meter subplot was selected within each 12 acre plot by walking sufficiently far from roads or fence lines to an area in which vegetation appears homogenous, and tossing a 1m square constructed from PVC. Within the 1m plot, all herbaceous and woody plants were identified to species level, with percent cover recorded for each. Using a nested plot approach, a larger 5m subplot was sampled for all shrubs and all woody plants with a diameter at breast height (DBH) of <10cm. Finally, in a 25m subplot, the DBH, height, and condition of all woody vegetation with a DBH of >10cm was recorded (Figure 2).

Figure 2: Nested Plot Diagram



Source: UAS Ground Truthing Protocol, Boardman 2018. Adapted from Wertime et al. (2007).

Using vegetation data collected from plot-level sampling, a number of biodiversity metrics were calculated to quantify species richness (the count of unique species identified). Additionally, the Shannon index *(H)* was calculated as an indicator of species diversity for each subplot, using the formula:

$$H = -\sum_{i=1}^{S} p_i \ln{(p_i)}$$

where *S* represents the total number of species in each plot and P_i represents the proportion of *S* made up of the *i*th species (Magurran 1988).

The use of a variety of biodiversity indices is commonly recommended as a method of providing greater insights into the inter-species interactions and the causes of differing community composition (Morris et al. 2014). While species richness is the most straightforward metric and can be used as a basic indicator of the number of species in a given system, the Shannon index provides a metric of the heterogeneity or equity of species composition (Peet 1974). Although many studies have indicated that a diverse species assemblage (i.e., greater species richness) promotes temporal stability in grasslands (Isbell et al. 2011; Pennekamp et al. 2018), systems with more equal proportions of species (i.e., greater Shannon index) tend to be more stable than those with a dominant species (Sanderson 2010; Sasaki and Lauenroth 2011).

Because vegetation sampling represents a limited spatial extent and finite sample size, first-order jackknife and Chao 2 predictive estimates of species richness were prepared both at county-level and in pooled groups of landowner perceptions ("Encroached" and "Intact") (Magurran 1988). Estimates were generated using the EstimateS program with 100 randomizations and bias-corrected formulas for Chao 2, as recommended by Colwell (2013).

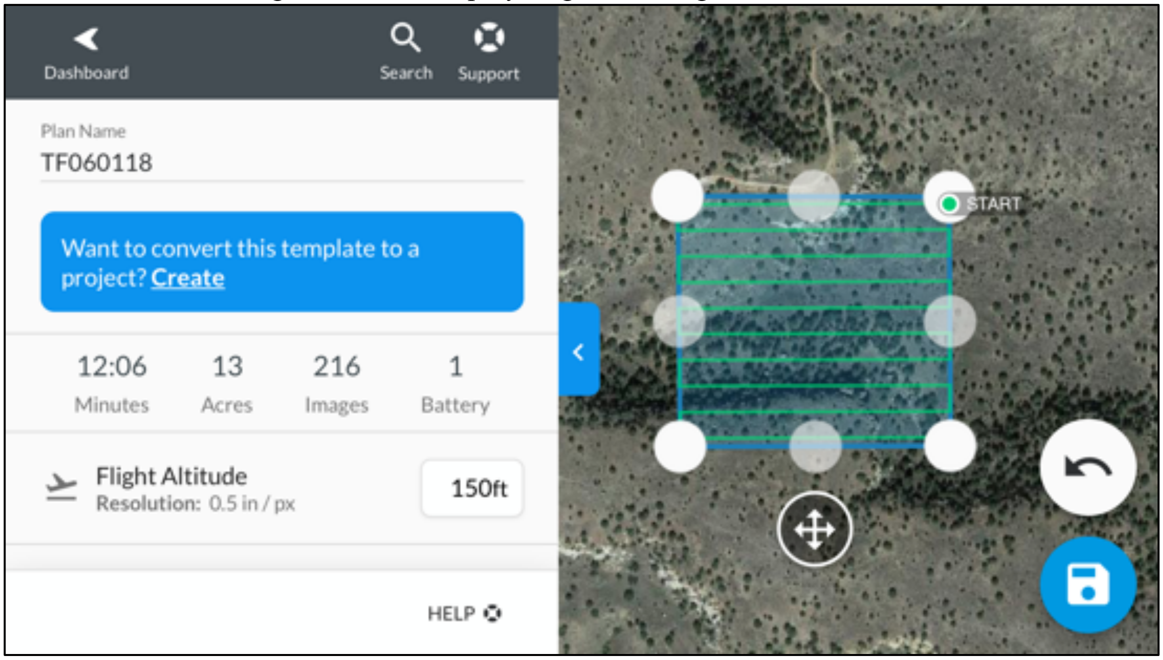
In addition to vegetation data, a number of rangeland characteristics and health metrics were collected, as described by Pellant et al. (2005). Characteristics of interest include description of livestock, percent bare ground, and slope, as well as a number of rangeland health indicators including the presence and severity of rills, water flow patterns, pedestals, gullies, erosion, and litter movement. Additionally, soil characteristics were documented as specified by IFRI (Ostrom 1999), including the depth of the O, A, and B horizons, the Munsell color, and the soil texture.

Field observation data was stored in a method similar to survey data, with forms entered into a Microsoft Excel spreadsheet. Results were then pooled at multiple scales of analysis, including county-level and by landowner perception (intact or encroached plots). Significant differences between groups were analyzed using two-tailed t-tests in Microsoft Excel and the software package R.

UAS Imagery Collection, Processing, and Classification

In an effort to collect data at broader spatial scales, while still capturing occurrences of individual plants and identifying vegetation to species level, UAS imagery was captured for each 12 acre plot, typically in tandem with vegetation sampling. All UAS missions were conducted between June 18 and July 12, 2018 to ensure consistent plant phenology. A DJI Phantom 3 Pro was used, equipped with a stock 1/2.3" CMOS RGB sensor, capable of obtaining an image resolution of 3000x4000 pixels. Missions were planned and executed using DroneDeploy, with 75% forward overlap and 65% side overlap used as the optimal parameters for SfM processing (Frazier and Singh 2018). Flight altitude was set to 150ft AGL, resulting in a spatial resolution of approximately 1.2cm. In some cases, terrain variation required a slightly higher altitude, up to a maximum of 200ft AGL. All flights were conducted in accordance with Federal Aviation Administration regulations by pilots certified under CFR Part 107 guidelines. When possible, missions were conducted between the hours of 1000 and 1400 local time with no cloud cover, to ensure optimal lighting conditions (as recommended by Watts et al. 2010). However, due to time constraints, other project requirements, and the large size of the study area, exceptions were sometimes made in extenuating circumstances.

Figure 3: DroneDeploy Flight Planning Interface on iOS

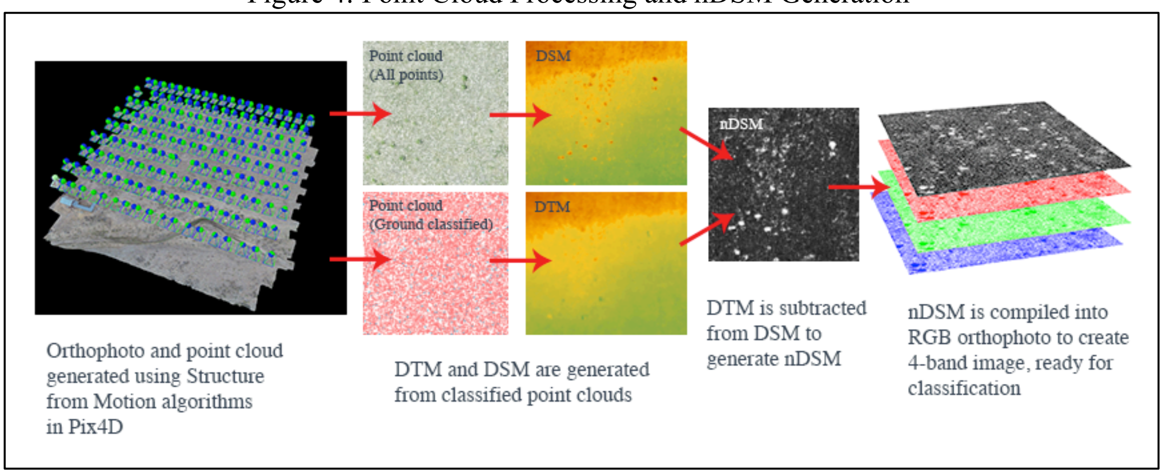


Imagery Post-Processing

Photos for each plot were merged into a single orthophoto using Pix4Dmapper photogrammetry software. Consistent with a participatory strategy, orthophotos were provided to landowners via an online portal, as a means of educating landowners on the extent of invasive and nuisance species on their property. Additionally, SfM-MVS algorithms in Pix4D generated dense point clouds depicting the 3D structure of terrain and features on the landscape (see Gillan et al. 2014).

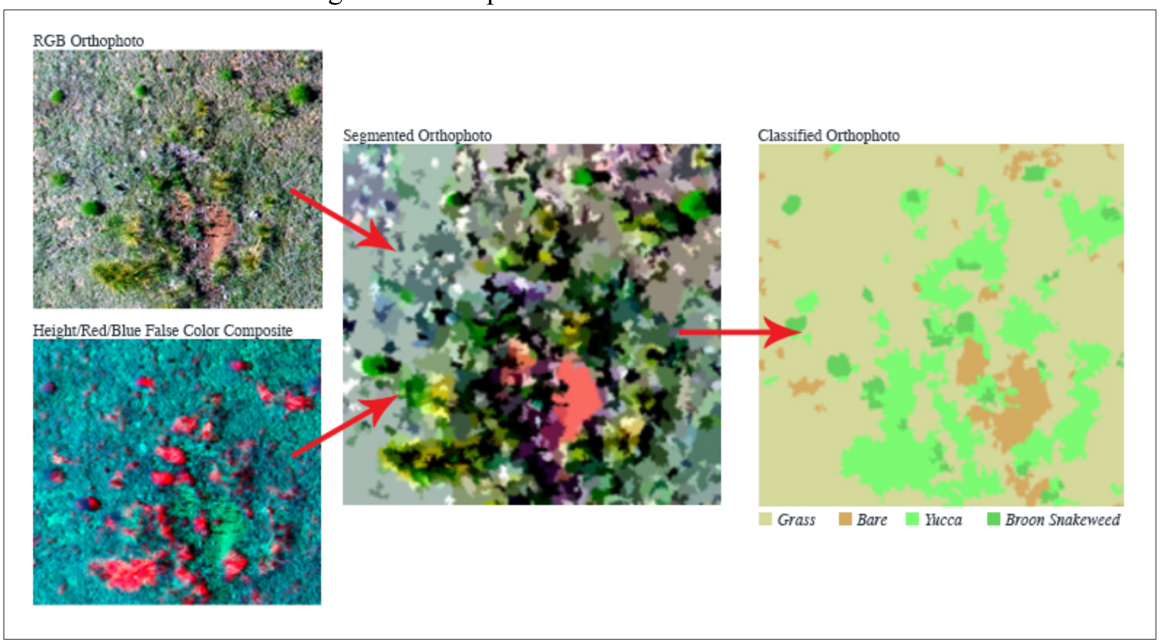
Because the UAS platform produced only 3-band RGB imagery, SfM-MVS-derived vegetation heights were merged as a fourth band in a DEM data fusion approach which has been shown to improve classifications (Alonzo, Bookhagen, and Roberts 2014; Ellis and Mathews 2019; Kabolizade, Ebadi, and Ahmadi 2010; Swatantran et al. 2011; Trinder and Salah 2012). To achieve this, dense point clouds for each orthophoto obtained from Pix4Dmapper were imported into a Python point classification script created by the author. The script utilizes tools in the 3D Analyst extension of ArcPy to classify points into ground and non-ground (full code shown in Appendix IV). Next, ground points were interpolated into a digital terrain model (DTM). Both ground and non-ground points were interpolated into a digital surface model (DSM). Finally, a normalized digital surface model (nDSM), representing the height of vegetation or other features on the plot, was generated by subtracting the DTM from the DSM using raster calculator (Li, Zhu, and Gold 2004). The nDSM was then merged as a fourth band in each RGB image (Figure 4) (Singh et al. 2012). In rare cases where terrain was too complex or vegetation too dense to produce an accurate nDSM through the Python script, some manual point classification was executed in ArcGIS Pro (Figure 5).

Figure 4: Point Cloud Processing and nDSM Generation



The final four-band orthophotos were then classified into land-cover classes using object-based image analysis (OBIA) in ArcGIS Pro. Individual segments, resulting from the OBIA, were grouped using a supervised approach. In order to most effectively compare UAS land-cover classes with ground-level vegetation sampling and household survey data, a separate classification scheme was created for each plot according the landowner's species of concern. For example, one plot may contain only two classes (e.g., grass and bare) if the landowner cited no nuisance species concerns, while another might contain five (e.g., grass, bare, cholla, yucca, and broom snakeweed) if all were cited as problematic by the participant. In instances where a nuisance species was cited, but did not occur in appropriate abundance for effective classifier training, such species were ignored.

Figure 5: Orthophoto Classification Workflow



Prior to classification, each orthophoto was clipped to remove any irregularities, including areas with edge effects (e.g., fences, roads, etc.), structures, or erroneous or noisy nDSM data. As a pilot to determine the most effective classification method, five randomly selected plots were classified using six unique approaches. For the first three approaches, segments in the 4-band imagery (with vegetation heights) were classified using (1) a support vector machine algorithm, (2) random forest classification, and (3) maximum likelihood classification. The next three approaches used the same three classification schema, but with 3-band RGB imagery (no vegetation heights). Each plot was segmented into "objects" of similar spectral values by modifying parameters in the ArcGIS Pro segmentation tool to optimize delineation of woody plants and bare soil from surrounding grass, while also minimizing the number of objects that comprised each patch (Laliberte et al. 2010; Rango et al. 2009). Next, training samples were collected for each land-cover type *(n = 10 × [number of bands] × [number of classes]) (Mather 2004)*. Finally, classification was executed on each set of orthophotos, segmented orthophotos, and training samples.

Classification accuracy assessments and confusion matrices were calculated by randomly placing points across each classified orthophoto *(n = 10 × [number of classes]*^{2}*)* (adapted from Mather 2004) and manually determining the appropriate land-cover class for each point based on the apparent class shown in the high resolution imagery (Stehman 2009). While separate reference data such as ground-truthed points or aerial photographs are often consulted for accuracy assessments in coarser resolution imagery, visual inspection alone is adequate for ultra-high resolution imagery (Husson, Ecke, and Reese 2016). This approach has been shown to identify vegetative land cover to species level with 95% accuracy (Husson, Hagner, and Ecke 2014).

Once the most accurate classification method was determined, all 40 UAS orthophotos were classified and assessed for accuracy using the same protocol. In instances where overall accuracy fell below 85% (threshold set by Anderson 1976), orthophotos were reclassified until either the threshold was met, or three attempts were completed. Accuracy metrics including user's accuracy (errors of commission or "map reliability"), producer's accuracy (errors of omission), and total accuracy (the percentage of correctly classified points) were calculated for each plot from confusion matrices as described by Congalton (1999). Additionally, a Kappa statistic was calculated as a test of significant disagreement between classification and reference data (Monserud and Leemans 1992), where values of >0.8 indicate strong agreement, values between 0.4 and 0.8 indicate moderate agreement, and values below 0.4 are poor (Landis and Koch 1977).

Upon completion of classification and accuracy assessment, the total acreage and proportion of each land-cover class for each plot was calculated. These data were stored in a Microsoft Excel spreadsheet and were pooled at multiple scales of analysis, including county-level and by landowner perception (intact or encroached plots). Significant differences between groups were analyzed using two-tailed t-tests in Microsoft Excel and the software package R.

National Land Cover Dataset Change Detection

As the coarsest but broadest scale data source of this analysis, and the only temporally variable data, 30m resolution National Land Cover Dataset (NLCD) data was obtained from the years 1992 and 2016 to examine land-cover change across the entire extent of the study area. The 1992 dataset, as the oldest available version of NLCD, provides historical context for vegetation in the region during a period of normal precipitation (Fagin et al. 2016, 5). Comparing 1992 to 2016 provides an important time series both because 2016 represents a landscape emerging from a historic 15-year drought (U.S. Drought Monitor 2019) and is temporally the closest available data to UAS observations.

Using methods described by Fagin et al. (2016), the 1992 dataset was modified to conform to current NLCD classification categories using the NLCD 1992/2001 Retrofit Land Cover Change dataset (Fry et al. 2009). For both years, data was reclassified to a modified Anderson Level I classification scale (Anderson et al. 1976), which collapses NLCD categories into just seven groups, including three which are relevant to this investigation: herbaceous, forest, and shrubland. To quantify change in vegetation over time, the Raster Calculator tool in ArcGIS Pro was used to isolate pixels that converted from Herbaceous to Forest or Shrubland land-cover categories. The resulting raster layer exhibits the specific localities of woody plant encroachment from 1992 to 2016, albeit without details related to the exact species of concern.

NLCD Regression with Environmental Variables

To more clearly evaluate the role of environmental variables on plant communities, a spatial error regression model was implemented to directly measure the relationship between WPE severity and climate, terrain, and soil. Because land use undoubtedly also plays a role in WPE (Fagin et al. 2016; Vadjunec et al. 2018; Wenger, Vadjunec, and Fagin 2017), individual land parcels were implemented as the unit of analysis under the assumption that these parcels largely represent delineations of land management practices, since a single owner is likely to use the same judgements in making management decisions across the parcel. Further, despite changing management actions across parcel lines, environmental variables are typically consistent within the parcel extent.

To map these parcels, a 2018 Union County CAD file was purchased from the county GIS office and Cimarron County parcels were sourced from a 2014 paper plats and digitized as part of the larger project. Within each parcel, the percent vegetation change from the NLCD layer was calculated using the Zonal Statistics tool in ArcGIS Pro. Six climatic variables were obtained from the WorldClim Global Climate Database Version 2.0 (Fick and Hijmans 2017). WorldClim provides a global dataset of interpolated climate variables in raster format at 30 second resolution, which are frequently used in species distribution modeling and mapping (Beaumont, Hughes, and Poulsen 2005). For each of the six variables, the Zonal Statistics tool was used to calculate the mean value within each parcel. The variables used include Annual Temperature, Annual Precipitation, Temperature Seasonality, Precipitation Seasonality, Vapor Pressure, and Solar Radiation.

In addition to the six climatic variables, the role of complex topography on WPE was investigated. A metric of terrain ruggedness was calculated using the USGS National Elevation Dataset at 1/3 arcsecond resolution (USGS 2016a). A raster surface for slope in degrees was generated using the Slope tool in the ArcMap 10.4 Spatial Analyst toolbox, at the same spatial resolution as the original dataset. Within each parcel, standard deviation of slope was calculated using the Zonal Statistics tool, as a proxy for ruggedness. Additionally, soil data from the USDA SSURGO database (NRCS n.d.) was used to determine the role of soil texture variables including percent sand, silt, and clay.

Prior to use in regression, some variables were transformed to achieve a normal distribution, as needed. Because many of the environmental variables chosen for the model exhibit similar gradients across the study area, principal components analysis

(PCA) was implemented in SPSS v25 to reduce multicollinearity, using a varimax rotation to optimize component loadings. Finally, a linear regression special error model was created in Geoda 1.12 to interrogate the relationship between environmental variables and the severity of WPE. This special form of regression uses a spatial error component to account for spatial autocorrelation in the dependent variable and corrects for effects of unknown variables (Baltagi, Song, and Koh 2003).

Synthesis

While each of the three questions are addressed through independent data streams and methodologies, higher level conclusions will be drawn by examining the synergistic relationships between the various methods, especially in how they might relate to the uniqueness of the study area and exhibit geographic, scalar, and temporal variation. More specifically, synthesis of the multiple study components directly addresses Question 3 (*What are the benefits and limitations of multiple scales of analysis, particularly considering the potential role of unmanned aerial systems (UAS) as a scalar bridge in rapid vegetation assessments?)* by linking multiple spatial scales. Further, given the novel approach of UAS as a rapid assessment tool, using benchmarks of other rapid assessments provides contexts upon which to evaluate the efficacy of UAS in this study and LSS more broadly.

<u>Linking Household Surveys to Ground-Level and UAS-Level Vegetation Assessments</u>

Due to extensive research demonstrating how land management behaviors affect WPE severity (Archer, Schimel, and Holland 1995; Dullinger, Dirnböck, and Grabherr

2004; Van Auken 2009), relationships between household survey responses and vegetation community composition (at both ground- and UAS-level) were closely examined. Prior to analysis, survey responses were recoded in a variety of ways to reflect ecological relevance. For example, qualitative descriptions of past herbicide application were recoded into a binary variable (herbicide applied or not applied), the number of years since last application, or a count of the number of applications in the past ten years. Since no clear consensus exists on exactly which land management practices or frequencies best combat species invasions (Asner et al. 2004), all of these recoded responses were combined in a correlation matrix along with biodiversity metrics and UAS-derived land-cover proportions to identify potential trends. From this exploratory approach, t-tests were calculated in Microsoft Excel to examine whether the presence/absence of specific land management actions yielded significant differences in the land's vegetation and health.

Linking Ground-Level Vegetation Sampling to UAS Classification

Ultimately, the ground-level and UAS-level analyses sought to quantify many of the same metrics, including percent woody vegetation at species level, percent bare soil, and terrain variability. Notably, these metrics clearly influence each other, such as the well-documented relationship between bare soil and WPE (Allen and Allen 1991; Alofs and Fowler 2013) and between terrain complexity and some tree species (Coop and Givnish 2007). Additionally, other relationships, such as those between herbaceous plant biodiversity and woody plant abundance, are less clear (Levine 2000). To resolve these, and more directly answer Questions 2 and 3, linear regression was used to probe the relationship between biodiversity metrics (including species richness, diversity, and evenness) and the percent woody plant cover derived from each UAS flight. Additionally, results of ground-based and UAS-derived bare soil estimates and woody plant estimates will be compared, using a paired t-test to detect a significant difference between the two as described by (Laliberte et al. 2010).

Examining Differences between UAS and Coarse-Scale Satellite Imagery

A pitfall of satellite imagery is its poor resolution when compared to UAS, particularly because species of interest for this investigation are typically <3m in diameter, while NLCD data is obtained at 30m resolution. As a result, individual plants are not distinguishable, and land-cover classifications are determined based on the majority land cover (Xian et al. 2015). After obtaining percent woody plant cover for each UAS plot, percent shrubland/forest were derived for the same areas using NLCD data. The relative values were then compared using a paired t-test to determine whether NLCD data may under- or overestimate WPE. Additionally, linear regression was used to examine the relationship between the two. Residuals from the regression were mapped to identify whether there is a spatial pattern in NLCD classification error and metrics of spatial autocorrelation such as Moran's I were be calculated to determine if these patterns are statistically significant.

Summary

Because such a wide array of explanations have been proposed for desertification and changing vegetation communities in rangelands, a number of methodologies must also be implemented to examine which factors are most relevant in Cimarron and Union Counties. By starting with household surveys, issues of greatest importance to landowners provide context for all broader-scale analyses, and land management practices are directly evaluated. Further, the use of ground-, UAS-, and satellite-level detection of vegetation patterns provide a novel approach that both informs species distributions at multiple scales while also helping to evaluate the utility of UAS as a rapid assessment tool. Further, modeling of broad-scale environmental factors with satellite remote sensing provides a perspective on environmental effects to compliment the finer scale land management analysis.

As Chapter 4 (Results and Discussion) continues, the findings of each method are presented, with their relevance and relationship to others discussed in depth. The chapter then discusses the benefits and drawbacks of approaching this investigation through an LSS approach, detailing the ways that a more complete picture of causes and effects might be teased out of a mixed methods approach.

CHAPTER IV

RESULTS AND DISCUSSION

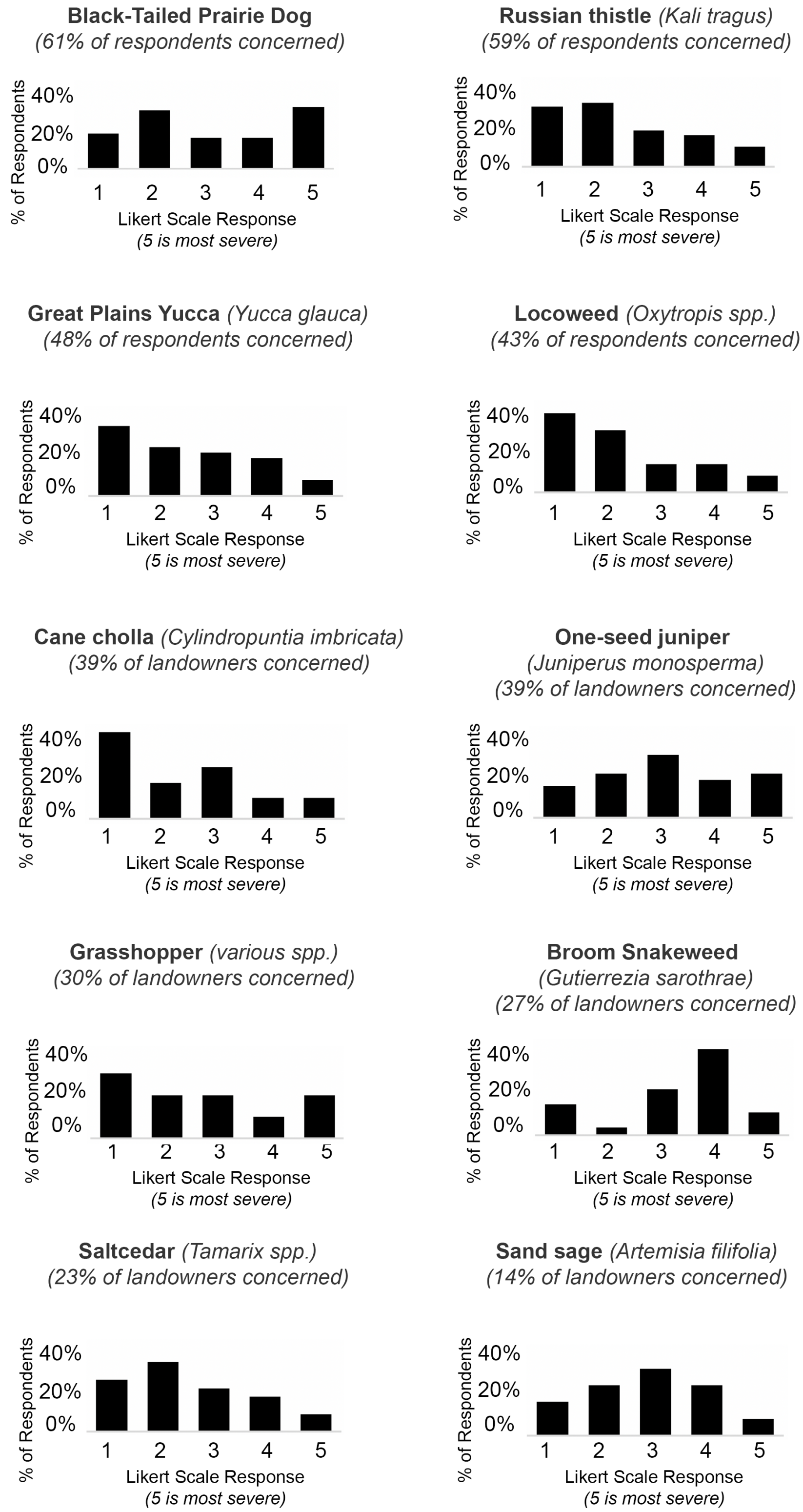
Household Surveys

Surveys were conducted with 20 household, 10 from each county. While the majority of respondents were cattle ranchers, four were farmer-ranchers, and two were farmers managing grasslands as part of the Conservation Reserve Program (CRP). Participants were 80% male and nearly all were long-term residents of the area.

Landowner Perceptions

Household survey questions related to landowner perceptions revealed that respondents have a keen knowledge of the landscape and the biophysical features that characterize it. Further, many survey respondents provided thoughtful answers related to invasive nuisance species, detailing not only which species occurred on their property, but what consequences its presence might have and what actions they have taken to reduce them. The most commonly cited nuisance species by landowners was black-tailed prairie dog. When asked whether or not they were concerned about the species, 61% of respondents indicated as a concern (Figure 6). Many landowners said the rodent disturbs soil and grass, and that burrows can cause injury to cattle that inadvertently step into them. As an additional non-vegetation concern, 30% of respondents named grasshoppers as a nuisance species on their property. Many claimed drought exacerbated the densities

Figure 6: Nuisance and Invasive Species of Concern among Landowners



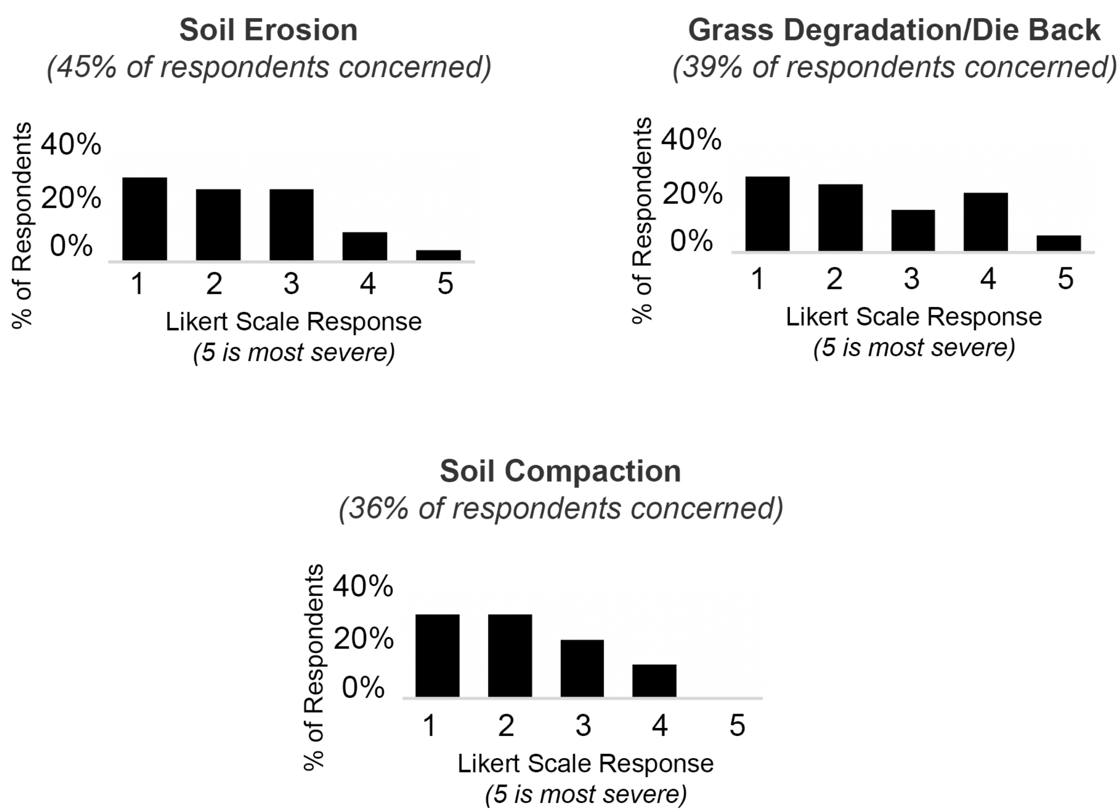
of the insect, which competes with cattle for forage. Of landowners who said they were "concerned" and were asked to rate the severity of each nuisance species on their property on a Likert scale (1-5, where 5 is most severe), respondents were more likely to rank these two species a "5" than any other species.

In terms of vegetation, the most commonly cited nuisance plant was Russian thistle (*Kali tragus)*, commonly known as tumbleweed. Although no landowners claimed deleterious ecological effects, the plant can become a management issue by damaging fences, creating fuel for fires, and even "high-centering your truck," as one respondent noted. Again, many said the species is more prevalent during drought. In a similar vein, locoweed *(Oxytropis spp. and others)* was mentioned by 43% of respondents as problematic because of its toxicity to cattle. Similarly, no larger ecological effects of the plant were mentioned, but many landowners have taken steps to remove the plant and the threat to their livestock.

Though landowners identified the aforementioned species as problematic, none were included in the remote sensing portion of this investigation due to low detection probability. However, several trees and shrubs cited by landowners were later identified in UAS imagery, including Great Plains yucca (*Yucca glauca*, 48%), cane cholla *(Cylindropuntia imbricata*, 39%), one-seed juniper *(Juniperus monosperma,* 39%), broom snakeweed *(Guterrezia spp.*, 27%), and sand sage (*Artemisia filifolia,* 14%). Notably, respondents tended to rate the severity of these species on the lower end of the Likert scale. Although surveyors asked specifically about each of these species, since they were documented as species of concern by Fagin et al. (2016), some respondents questioned characterizing them strictly as a "nuisance." For example, many landowners had observed Great Plains yucca on their property, but saw it as beneficial because cattle can eat the blossoms in early spring. Similarly, some saw a benefit in juniper and cholla on the landscape, as the plants can serve as a windbreak or snow fence in the harsh winters. However, despite these outliers, most respondents agreed that many woody species were becoming problematic as they left less grass for cattle.

A majority (76%) of landowners indicated they had experienced at least one of the three major types of land degradation mentioned in the survey, including soil erosion, grass degradation, and soil compaction, while 13% had experienced all three. The most commonly cited issue was soil erosion, affecting 45% of respondents, though most rated the severity on the bottom half of the Likert scale (Figure 7).

Figure 7: Land Degradation Issues among Landowners



In general, respondents indicated that maintaining healthy plant communities on their property involved high levels of effort. When asked, “How much effort have you put into removing nuisance/invasive species from your land?”, 75% of respondents gave a Likert ranking of 3 or higher, while 27% responded with a 5—the highest level of effort.

Land Management Practices

Land management practices for the 40 ground observation/UAS plots were somewhat variable (Table 1), though the most common land use by far was traditional cow-calf grazing with few modifications to the land. Twenty-nine plots grazed cattle at traditional stocking rates, while six more only used the pasture for short-term intensive grazing. Seven plots were registered under the Conservation Reserve Program (CRP), some of which were periodically grazed. Only four of the plots had been burned for nuisance plant management, while two had been mowed, and five had used herbicide applications. Two additional plots had undergone some light manual removal of invasive species. The vast majority of the plots were privately owned, though two were state leases.

At the county level, there was little difference in land-use/management practices among the 40 plots (Table 1). One state-owned plot was present in each county, while the remainder were privately owned. Grazing was the dominant land use in both counties, though one quarter of Cimarron County plots were enrolled in CRP, compared to just 10% of Union County plots. Land management practices did seem to differ across county lines. Four plots in Union County were burned and two had vegetation manually removed, though these practices were not used on any Cimarron County plots. By contrast, mowing occurred in two Cimarron County plots, but no Union County plots.

Landowners perceived both of the two state-owned plots as “Intact”. A majority of grazed plots were also “Intact”, though five of the seven CRP plots were perceived as “Encroached”. Management actions such as burning, mowing, and manual removal were fairly evenly split between the "Intact" and “Encroached” groups. However, 80% of plots with herbicide applications were identified as “Intact.”

Table 2: Plot Land-Use and Management Descriptions

		County-Level (# plots)		**Landowner Perception (# plots)**	
		Cimarron (OK)	**Union (NM)**	**“Intact”**	**“Encroached”**
Ownership	Private	19 (95%)	19 (95%)	18 (90%)	20 (100%)
	State	1 (5%)	1 (5%)	2 (10%)	0 (0%)
	Total	**20**	**20**	**20**	**20**
Land Use	Grazing	15 (75%)	18 (90%)	18 (90%)	15 (75%)
	CRP	5 (25%)	2 (10%)	2 (10%)	5 (25%)
	Total	**20**	**20**	**20**	**20**
Management Actions	Burning	0 (0%)	4 (20%)	2 (10%)	2 (10%)
	Mowing	2 (10%)	0 (0%)	1 (5%)	1 (5%)
	Herbicide	3 (15%)	2 (10%)	4 (20%)	1 (5%)
	Manual Removal	0 (0%)	2 (10%)	1 (5%)	2 (10%)
	Total	**5**	**8**	**8**	**6**

Ground-Level Observations

Forty plots for ground-level observations (and by association, UAS imagery) were distributed across Cimarron and Union Counties. Although though few plots were located in the primarily cultivated lands of eastern Cimarron County due to intensive land modifications in the areas, plots were systematically distributed across all other regions of the study area.

Biophysical Observations and Rangeland Health

Ground-level biophysical observations revealed a wide diversity in land quality and degradation, reflecting the varied responses of landowner perceptions regarding land quality. For example, the estimated percent bare soil within sampling plots ranged from 0% (i.e., totally covered in vegetation) to 70% (highly degraded). Plots varied dramatically in terrain features as well; many were completely flat, while the slope on others was estimated as high as 10°. In terms of rangeland health metrics, including presence of rills, water flow patterns, and pedestals, nearly all plots scored on the lower end of the 1-5 scale, indicating low degradation (Table 3). Rills were the most commonly identified indicator of degradation, occurring in 26 of the 40 plots at varying severities. Additionally, evidence of livestock was observed on 33 of the 40 plots.

Table 3: Ground-level Land Degradation Assessments

Metric	**All Plots**	**County-Level**		**Landowner Perception**	
		Cimarron (OK)	**Union (NM)**	**Intact**	**Encroached**
Percent Bare Soil	18 (16)	25* (18)	13* (12)	17 (17)	20 (14)
Estimated Slope	1.7° (3.1°)	2.4° (3.7°)	0.9° (2.3°)	2.2° (3.5°)	1.1° (2.5°)
Rills	1.7 (0.6)	1.6 (0.6)	1.8 (0.6)	1.7 (0.6)	1.7 (0.6)
Water Flow Patterns	1.5 (0.8)	1.5 (0.9)	1.4 (0.6)	1.3 (0.6)	1.6 (0.9)
Pedestals/Terracettes	1.4 (0.7)	1.5 (0.8)	1.4 (0.5)	1.4 (0.7)	1.5 (0.6)
Gullies	1.3 (0.8)	1.4 (1.1)	1.2 (0.5)	1.3 (0.7)	1.4 (1.0)
Wind Scoured or Deposition	1.2 (0.5)	1.2 (0.6)	1.1 (0.3)	1.2 (0.5)	1.2 (0.5)
Litter Movement	1.1 (0.3)	1.1 (0.4)	1.0 (0.0)	1.0 (0.0)	1.1 (0.4)

*All values displayed as means (standard deviations). *Significant difference between counties (p<.05)*

A wide range of soil types were also observed in ground observations. Coarser soil textures (e.g., coarse sandy, moderately coarse loamy) were more common, though 13 plots had moderately fine loamy soils. In nearly all plots, soil was extremely dry. O horizons were rarely present, and cores could not be driven into the B horizon due to dryness and compaction. Despite this, disturbance by prairie dogs was very common with networks of deep burrows often extending across and beyond entire plots.

Table 4: Soil Texture Classes

Soil Texture Class	**All Plots**	**County-Level**		**Landowner Perception**	
		Cimarron (OK)	**Union (NM)**	**"Intact"**	**"Encroached"**
Coarse Sandy	13 (33%)	9 (45%)	4 (20%)	5 (25%)	8 (40%)
Moderately Coarse Loamy	9 (23%)	5 (25%)	4 (20%)	6 (30%)	3 (15%)
Medium Loamy	1 (3%)	-	1 (5%)	-	1 (5%)
Moderately Fine Loamy	13 (33%)	6 (30%)	7 (35%)	6 (30%)	7 (35%)
Clayey	4 (10%)	-	4 (20%)	3 (15%)	1 (5%)
Total	40	20	20	20	20

At the county level, bare soil was significantly more severe in Cimarron County than in Union County *($t=2.41$, $p<.05$),* with bare soil exceeding 20% in nearly half of Cimarron County plots (Table 2). For other rangeland health indicators, Cimarron County plots tended to have slightly higher scores on average, indicating greater degradation, though the difference between counties was not significant. Sandier soils were more commonly observed in Cimarron County, where the most common soil textures were "sand," "loamy sand," and "sandy loam." By contrast, soils were more variable in Union

County, with “clay loam” and “silty clay loam” observed as the most common textures (Table 3).

There was no significant difference in rangeland health indicators between “Intact” and “Encroached” plots, though mean scores for percent bare soil, water flow patterns, pedestals, and gullies were slightly higher. Additionally, a full spectrum of soil types were observed in both Intact and Encroached plots. Therefore, differences in soil and rangeland indicators appear to be more important at county-level scale than household scale.

Vegetation and Biodiversity

Sixty-one unique plant species were identified during vegetation sampling across the 40 plots (Appendix VI). Predictive estimates of study area-wide species richness reached 68 (Chao 2) or as high as 73 (first-order jackknife) (Table 5). Notably, these values are much lower than the hundreds of species identified in county-wide vegetation surveys (Oklahoma Vascular Plants Database 2019, New Mexico Biodiversity Collections Consortium 2019), though these estimates represent minimum species richness values (Chao et al. 2009) and are based only on small n sampling in specific agricultural rangelands. Elsewhere, species richness in Great Plains tall- and midgrass prairie systems has been observed in the range of 100-300 (Risser 1988). Species richness in semi-arid shortgrass prairies is often at the low end of this range, though over 50 species have been observed in a single shortgrass prairie plot (Singh, Bourgeron, and Lauenroth 1996). Taken together, this suggests that species richness in Cimarron and Union Counties is likely greater than predictive estimates.

Most plots contained an assemblage of at least one warm season shortgrass (e.g., buffalograss or blue grama), often accompanied by one or more forbs (e.g., *Plantago patagonica* or *Ambrosia psilostachya*). The most common grass was buffalograss *(Buchloe dactyloides)*, occurring in 23 of the 40 plots, followed by blue grama *(Bouteloua gracillis)* in 15 plots. Cool season grasses were not as commonly observed; for example, western wheatgrass *(Pascopyrum smithii)* was identified in just 5 plots and needle-and-thread (*Stipa comata)* in just 2. Additionally, 9 plots had positive IDs for a species of locoweed. Many plots also included members of the Fabaceae family, including wild alfalfa *(Psoralea tenuiflora)* and yellow clover *(Melilotus officinalis)*, many of which serve important ecological functions such as nitrogen fixation. Woody plants, including trees such as one- seed juniper *(Juniperus monosperma),* shrubs such as broom snakeweed (*Gutierrezia spp.)*, and cacti such as cane cholla *(Cylindropuntia imbricata)* and yucca *(Yucca glauca)* were identified in 32 of the 40 plots (hereafter, referred to as "woody plots"). Broom snakeweed was by far the most common woody plant, observed in 17 plots. By contrast, the next most common woody plants were prickly pear (7 plots) and yucca (6 plots). The majority of woody plots (21 of 32) hosted just one woody species, though as many as six woody species were observed in one highly diverse riparian plot.

No clear patterns emerged between herbaceous biodiversity and woody vegetation. Although there was a significant positive relationship between Shannon Index obtained at the 1m and 5m plots (Figure 7B), 1m plots frequently contained some woody species (especially broom snakeweed), and therefore cannot be used as a proxy for herbaceous vegetation.

Table 5: Plot Biodiversity Metrics

			All Plots	County-Level		Landowner Perception	
				Cimarron (OK)	**Union (NM)**	**"Intact"**	**"Encroached"**
1m Plots (All Species)	*Species Richness*	Mean (S.D.)	4.20 (1.90)	4.3 (1.87)	4.1 (1.92)	3.95 (1.63)	4.45 (2.11)
		Range	1 - 8	1 - 8	2 - 8	2 - 8	1 - 8
	Species Richness Estimates	Jackknife 1	73.45 (4.83)	58.05 (4.46)*	39.35 (3.45)*	56.90 (5.32)	59.95 (4.46)
		Chao 2	68.09 (9.09)	52.50 (7.64)*	37.59 (7.86)*	60.36 (14.01)	59.95 (11.64)
	Shannon Index	Mean (S.D.)	0.80 (0.36)	0.77 (0.39)	0.73 (0.39)	0.67* (0.31)	0.92* (0.36)
		Range	0 - 1.58	0 - 1.58	0 - 1.58	0.14 - 1.22	0 - 1.58
	Species. Richness (Poaceae)	Mean (S.D.)	1.53 (0.63)	1.45 (0.59)	1.6 (0.66)	1.4 (0.66)	1.55 (1.4)
		Range	0 - 3	0 - 2	1 - 3	0 - 3	0 - 6
5m Plots (Woody Species)	*Species. Richness*	Mean (S.D.)	1.38 (1.26)	1.55 (1.53)	1.2 (0.87)	1.2 (1.08)	1.55 (1.4)
		Range	0 - 6	0 - 6	0 - 3	0 - 4	0 - 6
	Shannon Index	Mean (S.D.)	0.19 (0.17)	0.19 (0.19)	0.19 (0.15)	0.17 (0.14)	0.21 (0.2)
		Range	0 - 0.67	0 - 0.67	0 - 0.58	0 - 0.51	0 - 0.67

**Significant difference between groups (p<.05)*

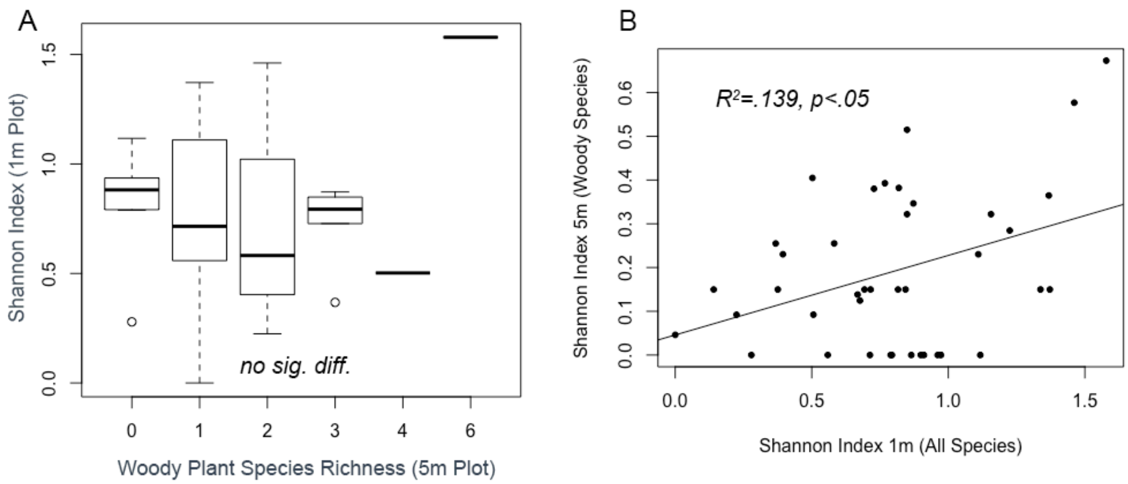
As with physical landscape data, biodiversity metrics for the 40 plots were likewise highly variable (Table 4). Species richness in 1m plots ranged from 1 (indicating just one species present) to 8, with a median of 4 and a slight right skew to the distribution. Shannon index for 1m plots ranged from 0 (indicating one species; i.e., no diversity) to a maximum of 1.58. The mean Shannon index value was 0.80, with a standard deviation of 0.36, consistent with species evenness metrics observed in similar semi-arid systems (Brockway, Gatewood, and Paris 2002; Knapp et al. 2002). For the 5m plots, where only woody plants were recorded, Shannon index values were lower, ranging from 0 to 0.67. The distribution was heavily skewed right, with 11 of the 40 plots exhibiting a 5m Shannon index value of 0 indicating no woody vegetation.

A significant difference in many rangeland health indicators was observed between woody and non-woody plots. Woody plots were significantly more likely to have more severe rankings for water flow patterns *($t=-2.09$, $p<.05$)*, pedestals/terracettes *($t=-4.19$, $p<.05$)*, and wind scouring/deposition *($t=-2.24$, $p<.05$)*. Additionally, woody plots on average had 8% more bare soil area *($t=-2.05$, $p<.05$).* However, no relationship was detected between soil texture and presence of woody plants *($X^2 = 2.78$, $p=0.952$),* nor between soil texture and Shannon index *($t=-1.33$, $p=.192$).*

County-wide species richness estimates were significantly higher in Cimarron County than Union County, as observed both by the first-order jackknife and Chao 2 estimates. However, plot-level difference of means tests revealed no significant differences between counties in woody vegetation diversity, nor in woody cover. Cimarron County plots on average had 9.1% woody cover, compared to 8.3% in Union County plots.

“Encroached” plots had significantly greater Shannon index values for 1m subplots than “Intact” plots *(t=2.23, p<.05)*. Additionally, “Encroached” plots were home to 0.35 more woody species than “Intact” plots, though there was no significant difference in proportion of woody cover between the two plot types.

Figure 8: Woody Plant Species Richness vs. Shannon Index



UAS Imagery Classification

<u>UAS Classification Accuracy Assessments</u>

In the initial pilot study to evaluate the optimal classification methods for UAS imagery, the Support Vector Machine (SVM) algorithm performed most accurately, and was improved by the addition of the fourth band containing vegetation height data (Table 5). The Random Forest (RF) method without height data was least accurate, with an average classification accuracy of just 80.3%. In both the SVM and RF tests, 4-band imagery with height data significantly increased classification accuracy by 3.2% on average, compared to RGB imagery *(t=3.27, p<.01)*. Results were mixed for Maximum

Likelihood Classification, however. Based on the results of this assessment, the SVM with heights method was implemented for all 40 UAS images.

Table 6: Accuracy of Various Classification Methods

Classification Method	**RGB** **Total Accuracy** *Mean (S.D)*	**RGB + Heights** **Total Accuracy** *Mean (S.D)*
Maximum Likelihood Classification	82.5% (3.5%)	80.7% (7.3%)
Random Forest	80.3% (7.1%)	83.5% (4.0%)
Support Vector Machine	84.4% (4.1%)	92.7% (2.3%)

Total accuracy of SVM classification in the 40 UAS images ranged from 81% to 97% *(μ=88.9%, σ=4.5%),* with 32 of the images meeting the desired 85% accuracy benchmark (Table 6). The mean Kappa value was 70.9% *(σ=9.5%),* suggesting moderate agreement in general between SVM classification and human identification, though classification for seven plots indicated strong agreement (Kappa > 0.8). Classification schema and categories varied depending on the species of interest cited by landowners. In half of plots, classification schema included just three classes (grass, bare, and one woody plant species), while 13 plots were classified into four classes, six plots had five classes, and one plot had six classes. While there was no significant relationship between the number of categories and the total accuracy, anecdotal observations suggest that SVM performed more poorly when two spectrally similar species (e.g., broom snakeweed and juniper) were present in the same plot. Additionally, plants with complex structure and texture (e.g., juniper or mesquite, with distinct patches of gray branches and green foliage) tended to result in inaccurate, patchy classifications. In fact, total accuracy in plots with juniper or mesquite present was 3.5% lower than in plots without *(t=2.12, p<.05)*.

Table 7: UAS Image Classification Accuracy Assessment

		Mean	St. Dev.	Number of Plots
Total Accuracy		88.9%	4.5%	40
Kappa		0.709	0.095	40
User's Accuracy	*Bare*	72.0%	19.0%	40
	Grass	95.0%	5.0%	40
	Snakeweed	75.0%	24.0%	21
	Yucca	35.0%	17.0%	18
	Sage	86.0%	18.0%	5
	Clover	70.0%	—	1
	Cholla	58.0%	22.0%	7
	Juniper	78.0%	19.0%	12
	Mesquite	58.0%	2.0%	2
	Water	70.0%	—	1
	Cottonwood	97.0%	—	1
Producer's Accuracy	*Bare*	79.0%	19.0%	40
	Grass	91.0%	7.0%	40
	Snakeweed	84.0%	14.0%	21
	Yucca	83.0%	18.0%	18
	Sage	72.0%	10.0%	5
	Clover	78.0%	—	1
	Cholla	96.0%	8.0%	5
	Juniper	87.0%	12.0%	12
	Mesquite	70.0%	10.0%	4
	Water	100.0%	—	1
	Cottonwood	81.0%	—	1

At the class level, the Bare Soil class had a user's accuracy of 72%, but a producer's accuracy of 79%, indicating the class was frequently overestimated. By contrast, the Grass class was slightly underestimated, though generally more accurate, with a user's accuracy of 95% and a producer's accuracy of 91%. Reliability of classification of woody plants, as indicated by user's accuracy, was moderate *(μ=69.8%,*

σ=16.9%), but was observed as high as 97% (cottonwood). The lowest reliability was observed for yucca (35% user's accuracy), which was frequently segmented into many objects because of its textural inconsistency and was often confused for grass due to its low height and spectral similarity. For most woody plant species, SVM overestimated coverage, as indicated by higher producer's accuracy (i.e., lower errors of omission). Misclassifications frequently occurred in shadows or in areas where segmentation could not distinguish spectral differences between foliage and neighboring grass. Sand sage, a species that was underestimated, tended to be confused for grass particularly in areas where there was little difference in height between the two classes.

UAS-Derived Land Cover

UAS images, as with ground observations, were varied in their coverage of bare soil, woody plants, and grass. Bare soil coverage in plots was generally low *(μ=9.1%, σ=9.8%)*, though was reported as high as 53%. Woody plant cover ranged from 1% to 29% *(μ=9.4%, σ=8.3%),* while grass was the dominant cover in all but one plot *(μ=81.5%, σ=16.0%)*. Broom snakeweed was the most commonly observed woody species in UAS images, occurring in 21 of 40 plots, followed by yucca in 19 plots, and juniper in 11 plots. Cottonwood, though observed in just one plot, occurred in the greatest density, occupying 14.1% of a single plot. Additionally, mesquite covered on average 10.3% of the four plots where it was present, while sand sage occupied 8.5% of the five plots where it was present. Other more commonly observed woody species were more moderate in their densities, with yucca covering just 5.6% on average, followed by juniper (4.8% coverage), broom snakeweed (4.4% coverage), and cholla (4.2%).

Table 8: UAS Image Classification Results

	All Plots	County		Landowner Perception	
		Cimarron (OK)	**Union (NM)**	**Intact Plots**	**Encroached Plots**
Acres	14.4 (3.1)	14.2 (3.2)	14.6 (3.0)	13.8 (2.6)	15.1 (3.4)
# Classes	3.7 (0.8)	3.7 (0.8)	3.7 (0.8)	3.8 (0.8)	3.6 (0.8)
% Woody	9.4 (8.3)	10.4 (8.6)	8.4 (8.1)	8.2 (6.9)	10.6 (9.5)
% Bare	9.1 (9.8)	9.8 (11.9)	8.5 (7.2)	7.4 (6.2)	10.8 (12.3)
% Grass	81.5 (16.0)	80.0 (18.1)	83.1 (13.5)	84.5 (11.9)	78.6 (18.8)

All values presented as means (standard deviations). No significant differences were detected between means at either grouping level.

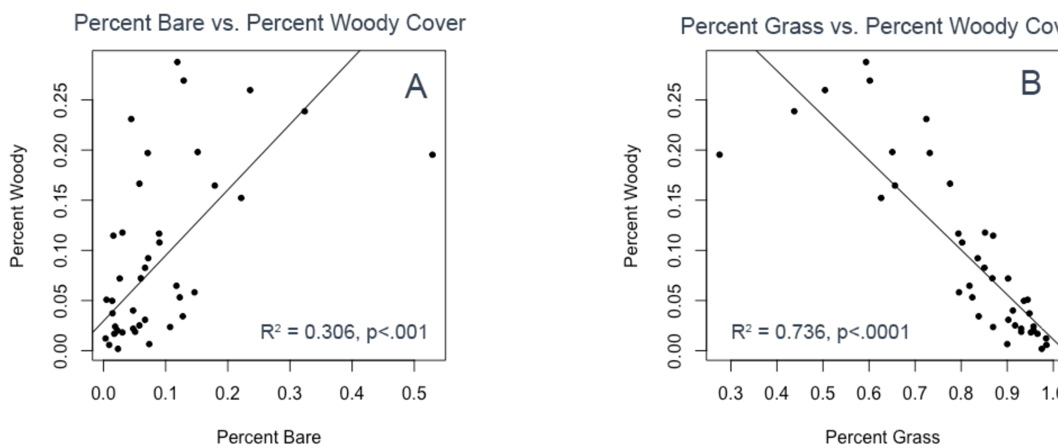
At the county level, UAS imagery classification revealed no significant difference between counties in coverage of grass, bare soil, nor overall woody plant cover (Table 7). However, certain species-level differences were observed. Broom snakeweed was observed in fourteen Union County plots, but just seven Cimarron County plots. Further, the species exhibited significantly greater coverage in Union County, occupying 4.3% of plots on average, compared to just 0.4% in Cimarron County ($t=2.93, p<.05$). By contrast, yucca coverage was significantly greater in Cimarron County ($\mu=4.3\%, \sigma=6.5\%$) than in Union County ($\mu=1.0\%, \sigma=1.5\%; t=2.07, p<.05$).

Although no significant differences were observed in land cover between "Encroached" and "Intact" plots, "Encroached" plots had slightly higher mean woody cover values ($\mu_{Encroached} = 10.6\%, \mu_{Intact} = 8.2\%$) and higher bare soil values ($\mu_{Encroached} = 10.8\%, \mu_{Intact} = 7.4\%$).

Supporting the notion that bare soil patches indicate land degradation, and therefore may cause the landscape to be more susceptible to woody plant encroachment, percent bare soil was significantly positively correlated with woody plant coverage (Figure 8A, $R^2=.306, p<.001$). There was no relationship, however, between the number of woody plant species classified and bare soil coverage ($F=.482, df=39, p=.697$).

Additionally, grass coverage was significantly negatively correlated with woody plant coverage (Figure 8B, *R^2=.736, p<.0001)*.

Figure 9: Relationships between UAS-Derived Land-Cover Classes

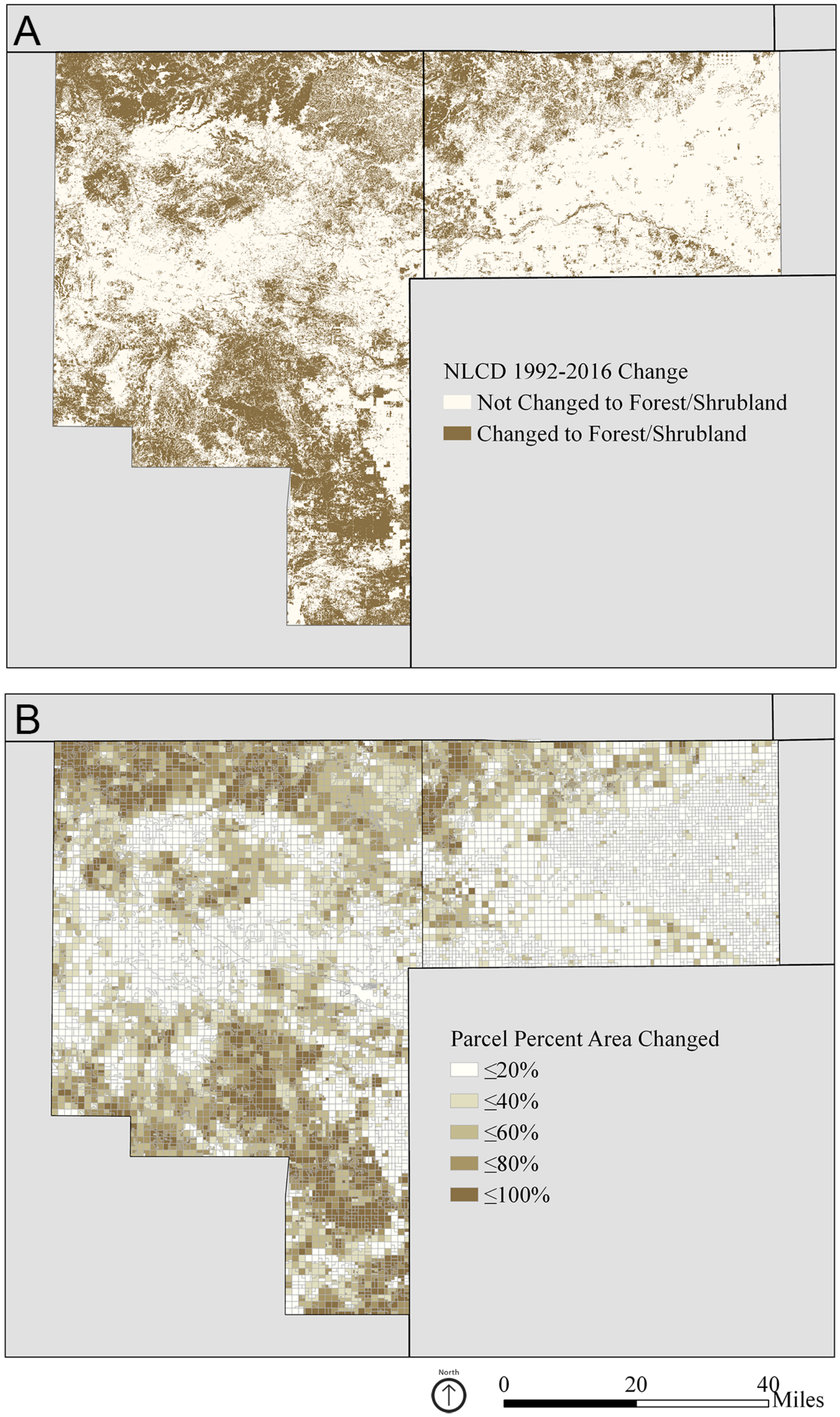


National Land Cover Dataset Regression

Comparisons of shrubland and forest coverage between the 1992 and 2016 National Land Cover Dataset (NLCD) revealed that 990,352 acres within the study area were encroached by woody vegetation, comprising 33.2% of Union and Cimarron Counties.

WPE was more severe in Union County, where 40.4% of land was converted to a woody land-cover class, compared to just 18.1% in Cimarron County (Figure 9). Further, encroachment was not only more severe overall for Union County, but tended to affect a greater proportion of landowners' parcels than in Cimarron County *(t=-49.364, p<.0001)*. Large portions of Cimarron County experienced little-to-no increase in shrubland or forest land cover, particularly in areas of cultivated agriculture. In fact, 33%

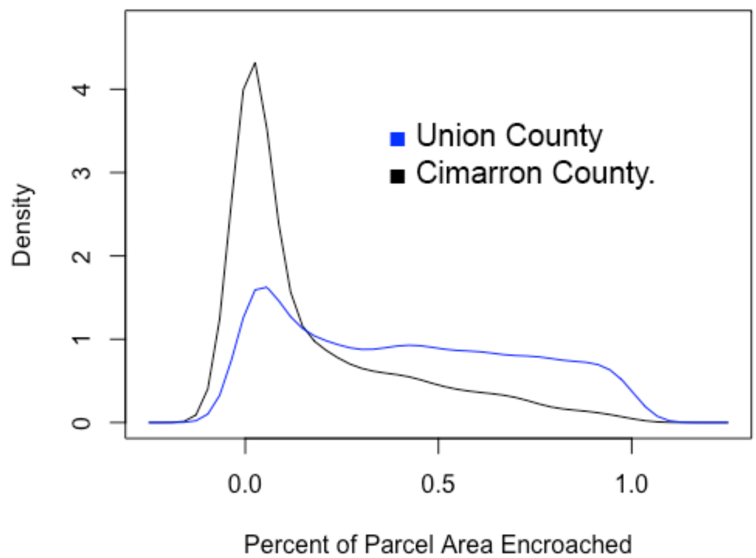
Figure 10: Change in Forest/Shrubland Cover from 1992-2016



Data sources: NLCD 1992 (Vogelmann et al. 2001), NLCD 1992-2001 Retrofit Product (Fry et al. 2009), NLCD 2016 (Yang et al. 2018), USGS State and County Boundaries (USGS 2014b, 2014a).

of Cimarron County parcels had no change in woody vegetation, according to NLCD data. By contrast, the same was true for just 4% of parcels in Union County. While encroachment intensity for Union County was still skewed right, with a greater proportion of parcels experiencing lower levels of encroachment, the likelihood of severe encroachment in Cimarron County was much lower (Figure 10).

Figure 11: County Comparison of Distribution of Parcel-level Percent Encroachment



Nine environmental variables were used in regression to predict WPE severity at he the parcel level: annual mean temperature, temperature seasonality, annual precipitation, precipitation seasonality, vapor pressure, soil percent sand, percent clay, and percent silt, and standard deviation of slope (a proxy for terrain ruggedness). Prior to regression, some variables were transformed or combined in a factor analysis to improve model performance and parsimony. The slope standard deviation variable was highly right skewed due to many parcels of land that had very little terrain variation. To improve normality of distribution, the variable was transformed using a square root transformation. Despite the skew of the percent encroachment variable, no transformation was implemented because neither a square root nor log transformation improved skewness and kurtosis metrics.

Additionally, soil texture data was comprised of three variables: percent sand, percent silt, and percent clay. Soils in the study area tended to range from sandy to silty-clay, showing a strong negative correlation between sand and clay *(r=-0.91)* and a positive association between silt and clay *(r=0.72)*. As a result, all three soil texture variables were collapsed into a single principal component, accounting for 90.6% of the variation in soil texture observed in the study area. For this principal component, low values were associated with sandier soils, while higher values were richer in silt and clay (Table 8).

Table 9: Soil Principal Component Description

	Component Loadings	Extraction Communalities
Percent Sand	-1.000	0.999
Percent Clay	0.919	0.845
Percent Silt	0.935	0.874

Similarly, strong multicollinearity was observed for several climate variables. Temperature was strongly positively correlated with temperature seasonality *(r=0.81)* and with vapor pressure *(r=0.97)*, indicating that warmer areas tend to have greater variability in temperature and greater vapor pressure (i.e., less evapotranspiration). Additionally, precipitation was inversely related to precipitation seasonality *(r=-0.71)*. To reduce multicollinearity in the final model, these five climate variables were merged into two principal components, accounting for 94.9% of variance in the climate data (Table 9). Higher values in PC1 were associated with warmer, more variable temperatures and with higher vapor pressure. Higher values in PC2 were associated with greater precipitation and less seasonal variability in precipitation.

Significant differences were observed between counties for all variables. Soils in Cimarron County were significantly sandier *($t=4.42$, $p<.0001$)* and the climate was warmer *($t=115.8$, $p<.0001$)* and wetter *($t=79.61$, $p<.0001$)*. Additionally, terrain was more rugged in Union County, with an average slope standard deviation of 2.53° per parcel, compared to 1.18° in Cimarron County *($t=-32.92$, $p<.0001$).*

Table 10: Climate Principal Components Description

	Component Loadings		Extraction Communalities
	PC1	PC2	
Temperature	0.989	0.028	0.979
Temp. Seasonality	0.831	0.509	0.950
Precipitation	-0.017	0.969	0.939
Precip. Seasonality	-0.480	-0.819	0.901
Vapor Pressure	0.973	0.168	0.975

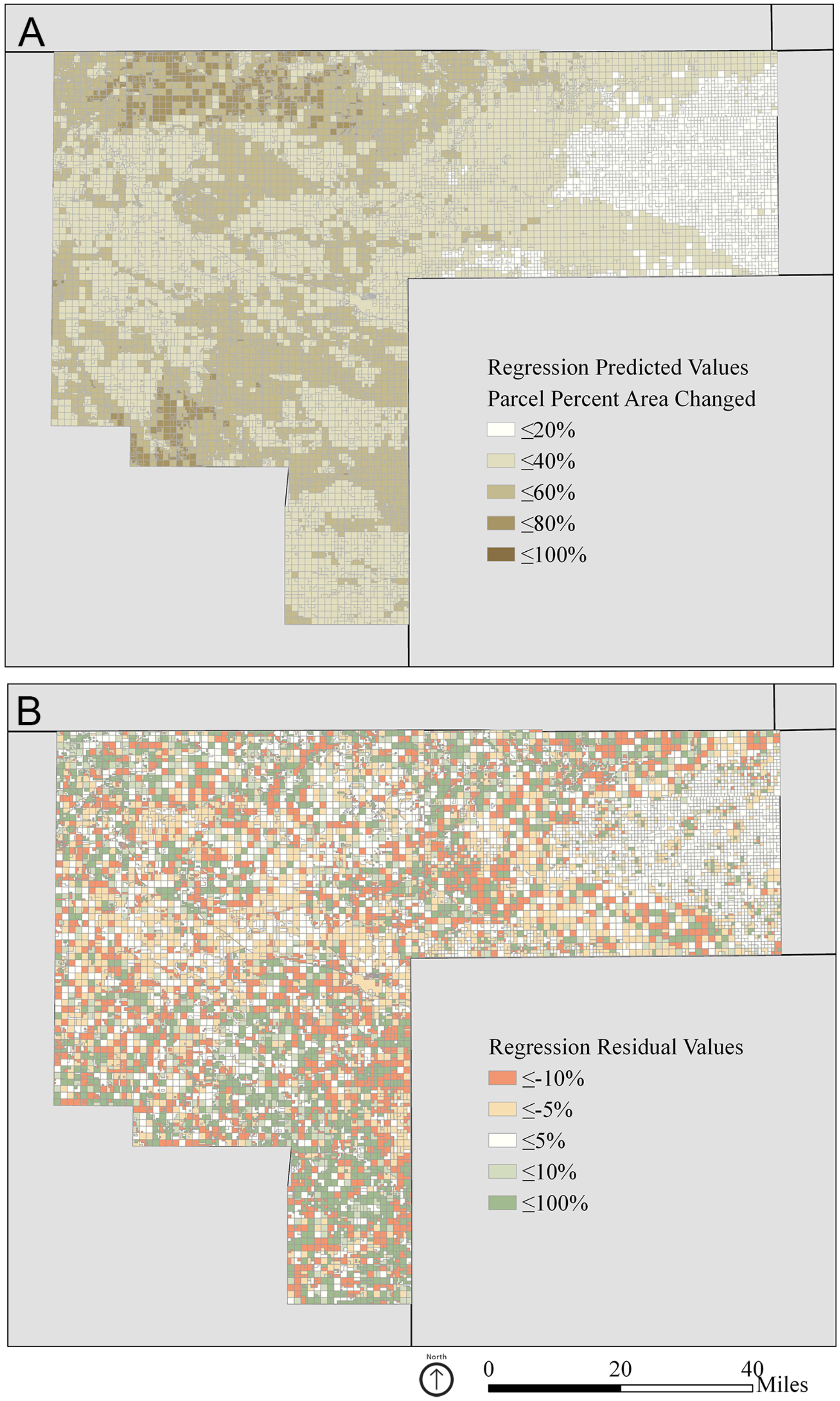
A total of 12,632 parcels distributed across the two-county study area comprised the units of analysis for regression (Figure 9B). The dependent variable, percent increase in woody vegetation from 1992-2016, was predicted strongly by just five model components (Figure 11A, *$R^2=0.783$, S.E.=14.3%, $F=1856.44$, $p<.0001$)*. The most significant environmental variable contributing to the model was slope standard deviation (e.g., terrain ruggedness), which was strongly positively associated with WPE (Table 11, *$z=30.24$, $p<.0001$)*. Soil texture was also strongly associated with WPE, with sandier soils being significantly more susceptible to tree and shrub encroachment *(z=-16.89, p<.0001).* Additionally, climate data was a strong predictor of vegetation change, with the most severe encroachment occurring in areas of cooler, more stable temperatures and lower vapor pressure *(PC1, z=-7.05, p<.0001)* and in drier areas with more variable precipitation *(PC2, z=-8.69, p<.0001)*. The strongest predictor of WPE according to the model was the spatial error component, lambda, which accounts for spatial autocorrelation between units of observation that are not explained by other variables.

Table 11: Contribution of Variables in NLCD Spatial Error Regression

Variable	Coefficient	Std. Error	z-value	Probability
Constant	0.201	0.009	21.37	0.0000
Slope S.D.	0.114	0.004	30.24	0.0000
Soil PC1	-0.052	0.003	-16.89	0.0000
Climate PC1	-0.056	0.008	-7.05	0.0000
Climate PC2	-0.065	0.007	-8.69	0.0000
Lambda	0.856	0.006	151.64	0.0000

Standard error of predicted values in the model was relatively low, at 14.3%. Residuals were randomly distributed across the study area *(Moran's I=-0.44*), through the lowest residuals were observed in areas where WPE was already low (Figure 11B). These areas tended to have lower sand content in soils, and were also often areas of cultivated land, particularly in Cimarron County.

Figure 12: NLCD Regression Output



Data sources: USGS State and County Boundaries (USGS 2014b, 2014a).

Synthesis

Because each method and result described above was measured through a unique scale and approach, similarities and differences have emerged that merit further inspection. As this section continues, different methods and results are directly compared to evaluate their levels of agreement or dissimilarity, both on a quantitative and qualitative level. Further, data is tested to examine how different metrics obtained through different methods may bridge together to form a more complete picture of how vegetation communities are changing.

<u>Linking Household Surveys to Ground-Level and UAS-Level Vegetation Assessments</u>

Due to low sample size for most land management variables (e.g., for mowing, $n=2$, for manual removal, $n=1$), survey responses were coded simply as binary variables, rather than year of action or frequency. Several moderate correlations were observed between management actions and land observations (Table 12). Grazing was positively correlated with all ground-level biodiversity metrics, providing evidence to support the beneficial ecological effects of "hoof action" cited by many survey respondents. Notably, these positive correlations held true both for herbaceous species biodiversity as shown in the 1m plots ($r=.27$), as well as woody plant diversity in the 5m plots ($r=.32$). Further, Shannon Index values for 5m plots (woody species) were significantly greater in grazed plots (Figure 12A, $t=2.72$, $p<.05$).

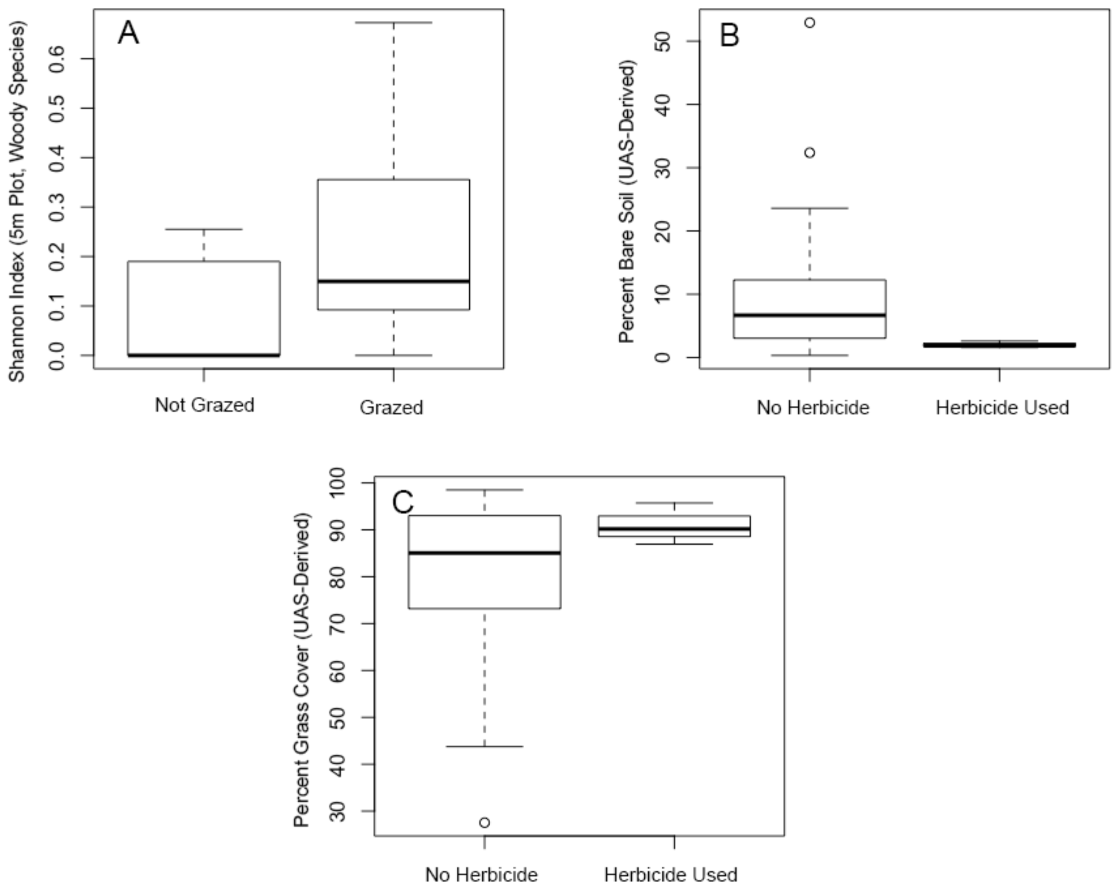
Table 12: Correlation Matrix of Land Use, Ground Observations, and UAS Land-Cover

	Land Use: Grazed	Land Use: CRP	Land Management: Burned	Land Management: Mowed	Land Management: Herbicide	Land Management: Manual Removal	Species Richness (All Plants)	Species Richness (Herbaceous Plants)	Shannon Index (1m, Herbaceous Plants)	Species Richness (Woody Plants)	Shannon Index (1m, All Plants)	Shannon Index (5m Plot)	Woody Species Present	Number of UAS Classes	UAS-Derived Percent Woody	UAS-Derived Percent Bare	UAS-Derived Percent Grass
Land Use: Grazed	1.00																
Land Use: CRP	**-0.43**	1.00															
Land Management: Burned	-0.04	-0.15	1.00														
Land Management: Mowed	-0.17	**0.20**	-0.08	1.00													
Land Management: Herbicide	0.14	-0.13	-0.09	-0.07	1.00												
Land Management: Manual Removal	0.08	-0.07	-0.05	-0.04	-0.05	1.00											
Species Richness (All Plants)	**0.25**	-0.01	-0.17	0.04	0.07	0.15	1.00										
Species Richness (Herbaceous Plants)	0.13	0.03	-0.14	**-0.22**	0.10	-0.16	-0.03	1.00									
Shannon Index (1m, Herbaceous Plants)	0.16	0.01	-0.09	**-0.37**	0.05	**0.20**	**0.55**	**0.20**	1.00								
Species Richness (Woody Plants)	**0.20**	-0.19	-0.03	0.02	-0.01	0.08	0.05	0.02	0.03	1.00							
Shannon Index (1m, All Plants)	**0.27**	-0.05	-0.16	-0.08	0.05	**0.30**	**0.81**	-0.04	**0.74**	0.11	1.00						
Shannon Index (5m Plot)	**0.32**	-0.13	-0.05	-0.04	-0.09	**0.35**	**0.31**	-0.02	0.16	**0.82**	**0.37**	1.00					
Woody Species Present	**0.22**	0.07	-0.04	0.11	-0.33	0.08	-0.01	-0.08	-0.12	**0.55**	-0.04	**0.55**	1.00				
Number of UAS Classes	0.05	**-0.23**	**0.23**	-0.06	-0.01	-0.14	**-0.25**	-0.18	-0.16	0.13	-0.16	0.06	0.12	1.00			
UAS-Derived Percent Woody	0.04	0.10	0.07	-0.01	-0.08	0.26	-0.04	0.03	-0.02	**0.49**	0.02	**0.60**	**0.41**	**0.31**	1.00		
UAS-Derived Percent Bare	-0.01	0.04	-0.01	0.11	**-0.20**	-0.08	0.07	-0.02	-0.17	0.34	-0.09	**0.27**	**0.32**	-0.05	**0.55**	1.00	
UAS-Derived Percent Grass	0.00	-0.07	-0.04	-0.06	0.17	-0.09	-0.02	0.00	0.12	**-0.46**	0.05	**-0.47**	**-0.40**	-0.13	**-0.86**	**-0.90**	1.00

n=40. Correlation coefficients shown in bold when -0.2<r<0.2. Significance not shown, as many variables were binary.

Plots managed through the Conservation Reserve Program (CRP, *n=7)* tended to have lower woody vegetation biodiversity (Table 12). Notably, species richness of trees and shrubs for CRP plots was significantly lower than grazed plots, as judged both by ground observations (*t=2.26, p<.05)*, and the number of woody species classified in UAS plots (*t=2.12, p=.051).* It was unclear, however, whether CRP had any effect on the severity of woody plant cover.

Figure 13: Significant Differences in Land Observations Based on Land Management



Herbicide application appeared to be the most effective management practice for increasing grass coverage. All landowners surveyed indicated that herbicide applications were strategically planned to target specific woody species, with no intended effects on herbaceous vegetation. While there was no relationship between biodiversity and herbicide use, bare soil coverage was significantly lower in treated plots *($t=4.50$, $p<.0001$)*, and grass coverage was significantly higher *($t=-2.73$, $p<.05$)*.

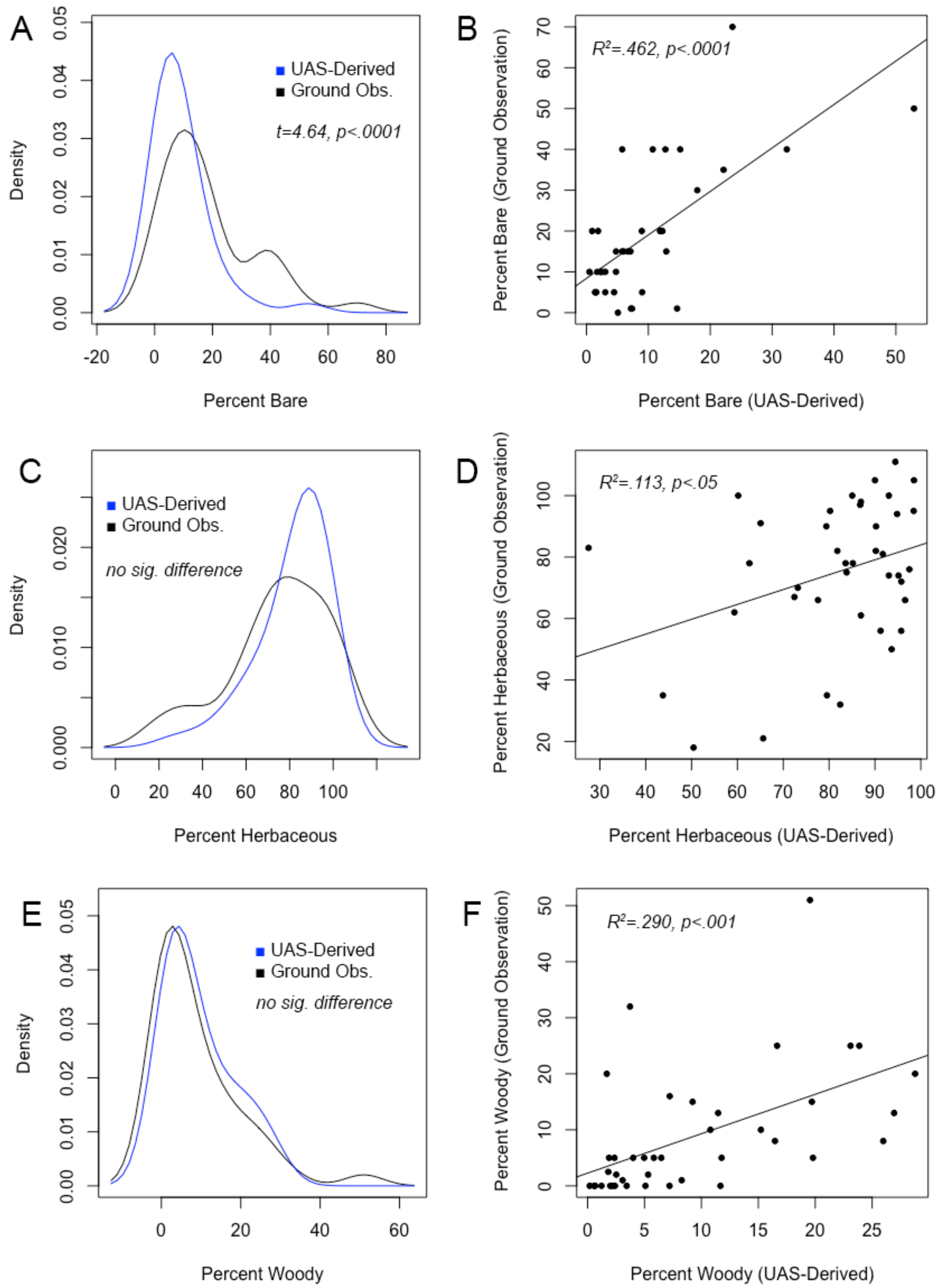
<u>Linking Ground-Level Vegetation Sampling to UAS Classification</u>

Land cover percentages estimated through ground-level observations were generally moderately correlated with UAS-derived metrics (Figure 13). Paired t-tests indicated that there was no significant difference between the two methods in estimates of herbaceous vegetation cover, nor woody vegetation cover. However, bare soil cover was greater in ground observations *($\mu =18.3\%$)* compared to UAS classification *($\mu=9.3\%$, $t=4.64$, $p<.0001$)*. Despite this, linear regression comparing the percent cover in each plot revealed that bare soil had the greatest correlation coefficient of the three classes (Figure XXB*, $R^2=.462$).* Woody vegetation coverage was less strongly correlated (Figure XXF, *$R^2=.290$),* followed by herbaceous vegetation (Figure XXD, *$R^2=.113$).* All correlations were significant at $\alpha=.05$.

As an additional observation regarding scale of analysis, UAS imagery tended to identify more woody plant species than ground observations, averaging 1.7 woody species per UAS plot *($\sigma=0.8$)*, while ground observations identified just 1.4 (*$\sigma=1.5$)*.

In terms of the relationship between biodiversity and UAS observations, a significant negative relationship was observed between UAS-derived herbaceous vegetation cover and the 5m Shannon index *($r=-0.47$)*, suggesting that herbaceous and woody cover are inversely associated. Similarly, a significant positive correlation was observed between UAS-derived woody vegetation cover and the 5m Shannon index

Figure 14: Comparison of Land Cover Percentages in Ground Observations and UAS Classification



(r=0.60), providing additional support for agreement between UAS- and ground-based vegetation observations.

Table 13: Correlation Matrix of Biodiversity Metrics and UAS Classification

	UAS-Derived % Bare	UAS-Derived % Grass	UAS-Derived % Woody	Species Richness	Shannon Index (1m Plots)	Shannon Index (5m Plots)
UAS-Derived % Bare	1.00					
UAS-Derived % Grass	-0.90**	1.00				
UAS-Derived % Woody	0.55**	-0.86**	1.00			
Species Richness	0.07	-0.02	-0.04	1.00		
Shannon Index (1m Plots)	-0.09	0.05	0.02	0.81	1.00	
Shannon Index (5m Plots)	0.27	-0.47**	0.60**	0.31	0.37*	1.00

*n=40. *Significant at p<.05; **Significant at p<.001.*

Examining Differences between UAS and Coarse-Scale Satellite Imagery

Parcel-level estimates for percent woody vegetation cover were significantly different depending on method of measurement. NLCD 2016-derived measurements of woody vegetation (i.e., shrubland or forest land-cover classes) were on average three times greater than those derived through UAS remote sensing (*t=4.14, p<.0001).* This observation held true both for Cimarron County *(μ_{NLCD}=29.9% μ_{UAS}=10.4%, t=2.56, p<.05)* and Union County *(μ_{NLCD}=30.9% μ_{UAS}=8.4%, t=3.27, p<.01).*

Linear regression comparing NLCD and UAS-derived woody cover for the 40 plots showed the correlation between the two methods was significantly stronger than random *(ANOVA F=7.20, df=39, p<.05)*, however the R^2 of 0.159 indicated a weak association overall. Standard error for regression was 0.320, indicating that the average difference in woody vegetation between the two methods was 32%—a remarkably high value considering the standard deviation between plots for UAS observations was just 8.4%. Plots located in areas of greater woody vegetation had greater disagreement between the two methods, as evidenced by moderate spatial autocorrelation of residuals *(Moran's I=0.445)*. However, there was no significant difference in residuals between counties. As with UAS-derived estimates, there was no significant difference in NLCD-derived woody cover between "Intact" and "Encroached" plots.

Discussion

Based on the rich array of data presented above, a number of conclusions may be drawn to help answer the three primary research questions of this thesis. Further, findings may be critiqued and additional commentary regarding the provenance, peculiarities, and prognosis of the data can be provided. As this section continues, interpretation and elucidation of the results are discussed, following the same order in which they were presented.

Household Surveys

Although household surveys focused primarily on vegetation, respondents indicated that species such as prairie dogs and grasshoppers were their greatest concerns. Notably, these species tended to increase in abundance over shorter periods of time, particularly during drought, and were generally more charismatic compared to nuisance plant species. This raises questions of potential retrospective bias (Pearson and Ross

1992) where survey respondents focus more heavily on recent observations, while forgetting older or more slow-changing observations. Further, the finding underscores the continuing importance of studying slow-onset disasters which may be more difficult to detect (Cutter 2005; Vadjunec et al. in review). Additionally, survey results reflect trends of science writ large, which tends to emphasize the importance of charismatic species (Donaldson et al. 2016). The relatively low severity scores for plant species represents dissonance between landowners and the range management literature, which is generally concerned about changing vegetation communities and typically emphasizes woody vegetation only as forage in extreme circumstances (Endecott et al. 2005; Wood, Mayeux, and Garcia 1990).

Of course, despite voicing worry about nuisance animals, many respondents did express concerns about woody vegetation and have taken extensive steps to remove these species. In fact, some respondents expressed disagreement with state agencies about the role of woody vegetation, which sometimes argue that it should be preserved as a wind break or natural snow fence. Thus, a wide range of opinions is present in the community indicating social science data is an undeniably powerful tool in gaining insights into the direct observations of those who use the land on a daily basis.

Soil erosion was the most common land management issue, according to respondents, which is consistent with the region’s historical association with dust storms. While changing land management practices such as no-till agriculture have reduced the severity of the issue (Lal, Reicosky, and Hanson 2007), respondents reported that ongoing drought has resulted in continued erosion.

Land-use practices were variable throughout the study area, though grazing was the most common. While landowners reported their typical grazing rates during surveys, the data was difficult to standardize into direct grazing impacts, since year-to-year and month-to-month stocking rates were highly variable and impacts were highly dependent on grass quality, precipitation, and other factors. All respondents expressed a desire to preserve their land through conservative grazing, particularly since many were tending to land that had been in their family for generations. Some respondents, however, voiced a concern about balancing financial needs with best grazing practices; stocking rates in some cases exceeded ideal numbers if a mortgage payment was due and there were no other forage options.

Another common land use, the Conservation Reserve Program, was observed for 18% of plots and was more common in Cimarron County. The program, which was designed after the Dust Bowl to help restore highly eroded lands, was almost universally praised by survey respondents but has had a mixed reception in the literature (Popper and Popper 1987). Notably, these lands were more frequently classified as "Encroached" by landowners, though woody plant cover biodiversity was lower on CRP lands than grazed lands.

Ground-Level Observations

Reflecting responses from landowners regarding their strategic prevention of land degradation, as well as the goals of the Conservation Reserve Program, land degradation across the study area was low. Rangeland health metrics indicated low occurrence of rills, gullies, wind scouring, and other evidence of degradation. Despite this, bare soil patches were remarkably high in some areas, reflecting many survey respondents' assessment that soil erosion was a major concern. In general, soil was very dry during sampling efforts, preventing examination of soils below the A horizon. All sampling was conducted during a period when most survey respondents said a drought was in progress, and surveyors witnessed multiple large dust storms during fieldwork. Generally, these storms and erosion appeared more severe in Cimarron County, where soil texture was coarser and cultivated agriculture is more prevalent. Consistent with these anecdotal observations, most rangeland health metrics were lower for Cimarron County.

Biodiversity metrics were consistently higher in "Encroached" plots, both in terms of herbaceous and woody vegetation. A significant association between land use and biodiversity was observed, though the specific relationship was not expected. The greater biodiversity in grazed lands contradicts literature arguing that livestock production reduces species diversity (Alkemade et al. 2013). Rather, it supports the idea that responsible, conservative grazing practices actually increase biodiversity in rangelands (West 1993). This considered, woody vegetation also contributes to biodiversity, therefore the role of livestock in contributing to healthy grazing lands is unclear.

Additionally, while CRP was intended to help conserve and improve land, and greater biodiversity is typically associated with greater rangeland health (Symstad and Jonas 2011), biodiversity was lower on CRP lands than on grazed lands. It is unclear whether this finding is due to reduced grazing, legacy effects, the application of prescribed seed mixes with limited species composition, or some other factor. Regardless, CRP lands did have lower proportions of woody plant cover.

There was not a clear link between herbaceous plant biodiversity and the presence/absence of woody plants. Past research has suggested that certain environments can support more diverse species assemblages, herbaceous or otherwise (Fridley et al. 2007), or that herbaceous species diversity confers some sort of protection against invasive species (Isbell and Wilsey 2011). In the present study, there were weak negative non-significant relationships between herbaceous species Shannon Index and the number of UAS classes *(r=-.16),* as well as between herbaceous Shannon Index and percent bare soil *(r=-0.17)*. Additionally, species richness was slightly lower in plots where woody species were present, though the difference was not significant. Factors affecting biodiversity may be associated with environmental variables, but also with land use since livestock can facilitate the spread of species across the landscape (Brown and Carter 1998). Additionally, seeding that sometimes occurs on CRP lands has been shown to reduce species richness compared to native pastures (Munson and Lauenroth 2012).

Overall, woody plots were more strongly associated with poorer rangeland health metrics. Notably, plots with a higher percentage of bare soil had greater species richness of woody vegetation. However, because this observation represents only one point in time, it is unclear whether bare soil patches create opportunities for species invasions (Bestelmeyer, Goolsby, and Archer 2011) or if the presence of woody species results in herbaceous vegetation declines (Hobbs and Mooney 1986). The answer to this chicken-and-egg question may vary from plot-to-plot or species-to-species.

UAS Imagery Classification

Based on the results of the pilot project, the Support Vector Machine algorithm demonstrated the greatest classification accuracy for UAS imagery, consistent with observations reported by Pande-Chhetri et al. (2017), Li et al. (2015), and Sonobe et al. (2014). Additionally, classification accuracy was improved through the addition of a DSM representing vegetation heights. In the present study, total accuracy increased by 3.2% compared to RGB alone—slightly higher than the 1.9% increase reported by Ellis and Mathews (2019) but less than the 16% increase in accuracy observed by Husson, Reese and Ecke (2017) for species with high spectral similarity.

Overall accuracy for the 40 plots was good, at 88.9%, and was on-par with or better than many other examples of species-level UAS imagery classifications (e.g., Husson, Reese and Ecke 2017, up to 85%; Pande-Chhetri et al. 2017, 70.8%; Sonobe et al. 2014, 89.1%). Thirty-two of the forty plots met the threshold of 85% total accuracy proposed by Anderson (1976). This considered, user's accuracy (errors of commission) for certain species was relatively low, particularly for species with highly variable heights or spectral composition such as the spiky yucca plant. However, the overall utility of UAS imagery for rangeland management should not be understated, particularly considering the high accuracy of grass and bare soil estimates, and the potential to dramatically improve species-level classification through hyperspectral imagery or the use of textural and shape data.

UAS data could reasonably considered the benchmark for data accuracy in this study, since land cover was measured objectively, the accuracy was evaluated thoroughly, and the data covers adequate spatial extents to avoid sampling bias from spatial heterogeneity. By contrast, ground observations for percent land cover were quickly estimated from ground-level and covered only a maximum area of 25 sq. m. Additionally, the 1992 NLCD accuracy was poor compared to UAS classification, averaging just 74% accuracy for the study area (Wickham et al. 2004).

According to UAS observations, densities of some woody species were remarkably high, with one plot exceeding 29% woody vegetation cover—effectively inhibiting any use for forage. Despite this, 39 of the 40 plots were dominated by herbaceous cover. Curiously, the woody species that occurred in the greatest densities tended to be ranked less severe by landowners. While the severity of juniper and broom snakeweed was more likely to be ranked a 3 or higher during surveys, these species occurred in the lowest densities. By contrast, sand sage covered 8.5% on average for the plots where it was observed. Yucca occurred on nearly half of plots, covering 5.6% on average, but more than half of landowners ranked it on the lower end of the severity scale. It is unclear whether landowners perceive other species (e.g., juniper, chollas) as more severe because of their height, an ecological effect, or some other factor.

A number of connections were observed between ground-level sampling and UAS woody plant detection. For example, the relationship between bare soil and woody vegetation was consistent whether observed at the ground-level, UAS-level, or cross-compared between methods. This finding holds true even when examining the phenomenon at county-level. Predictive estimates of species richness and UAS-derived estimates of woody cover were both higher for Cimarron County. This considered, a greater number of woody plant species were observed using UAS imagery, again highlighting the limitations of ground-level rapid assessments and providing additional support for the use of UAS as an effective rapid assessment tool.

In some cases, discrepancies arose when comparing ground-based and UAS-derived metrics. The apparent discrepancy between t-test and regression results indicates that ground-based bare soil estimates were consistently high relative to UAS-derived values. Meanwhile, greater residuals were observed for the herbaceous and woody vegetation cover, though they were more homoscedastic in their distribution, suggesting there was not a pattern of over- or underestimating coverage from plot-to-plot. One explanation for the differences in correlation coefficients between classes is the different measurement protocols implemented during ground observations. Per the ground observation protocol, bare soil was estimated for the entire UAS plot after walking around a sufficient area to make a reasonable assessment. By contrast, woody vegetation, with a lower R^2, was estimated just based on the 5m plot. Herbaceous vegetation, with a still lower R^2, was estimated from the 1m plot. Though ground observations required the survey area to be small enough for rapid assessment, the goodness of fit between ground- and UAS-based observations appears to diminish for data obtained in smaller plots.

While the data obtained through UAS is undoubtedly high in quality and provides a perspective and spatial extent not easily obtained through ground observations, the argument could be made that the method is not "rapid." While all flights for this project took less than 20 minutes each to complete, significant post-processing was required to produce data that could be directly compared to ground observations. Considering the time required to construct orthophotos from individual images, create point clouds, process points into ground and non-ground, create and composite nDSMs, segment images, select training samples, run algorithms, conduct accuracy assessments, and export statistics, the minimum post-processing time was 20 hours per image. Further, this process was repeated several times for many images if satisfactory results were not produced. By contrast, most ground observations were completed in under one hour of fieldwork with less than half an hour of subsequent species identification and data entry.

Although high resolution imagery has often been implemented for rapid assessments of vegetation (e.g., Blumenthal et al. 2007; Booth, Cox, and Berryman 2006; Sankey, Moffet, and Weber 2008), the utility of methods such as UAS is highly dependent on the desired measurements, methodology of analysis, and spatial extent at which data is collected. Notably, the nascent technology is not yet capable of identifying herbaceous vegetation to species in diverse systems. Therefore, while UAS imagery certainly has benefits in terms of the quality of data produced and potential for novel analyses, ground observations still have merit in obtaining detailed species-level data across small extents.

National Land Cover Dataset Regression

While ground observations and UAS imagery measured woody vegetation as a single snapshot in time, the NLCD portion of this analysis was unique in its examination of vegetation change over a 24-year period, from 1992 to 2016. Additionally, NLCD data continuously covered the entire study area, rather than small sampling plots. As a result, the overall severity of WPE across Union and Cimarron Counties could be distilled into a single metric of change. According to NLCD data, one-third of the study area was converted from shrubland to forest cover over the 25-year period of analysis, indicating dramatic change with substantial potential effects for agriculturalists. Land-cover change was more severe in Union County, contradicting UAS-derived land cover which showed higher woody cover in Cimarron County.

The multiple regression predicting severity of WPE performed well, accounting for 78.3% of variation in the data. While the high R^2 might be interpreted to indicate that environmental variables are 78% of the cause of WPE, a more nuanced explanation may also be valid. To this point, the spatial error component, lambda, which accounts for spatial autocorrelation in the data, nearly doubled the R^2; without incorporating lambda, environmental variable alone explain 42.4% of woody plant encroachment. While lambda could certainly account for unknown gradients in environmental variable, there is likely also spatial autocorrelation in land-use and management practices, as evidenced by household survey data. For example, perceptions of prescribed fire were generally much more positive in Union County than in Cimarron County. Despite the uncertainty in lambda, there is significant evidence that climate, soil, and terrain factors do influence the distribution of WPE severity. Therefore, certain parcels may be more vulnerable to vegetation change, suggesting the same land use/management on different parcels might result in different outcomes depending on the environment. Underlying this trend is an abundance of state school lands, which comprise approximately 20% of Cimarron County and 18% of Union County (Fagin et al. 2016, 4-5) and are often managed differently than private lands (Vadjunec and Sheehan 2010).

Terrain ruggedness was the most important environmental variable in the model. This metric is positively associated with topographic wetness index, a variable strongly linked to WPE in previous research (Fagin et al. 2016; Wu and Archer 2005). Soil texture was the next most important contributor. Sandy soils tended to have more severe WPE, likely because water drains more rapidly through coarser soils giving woody vegetation an advantage in water access compared to herbaceous vegetation (Knoop and Walker 1985; Walker and Langridge 1997; Wu and Archer 2005). These biophysical traits were also linked to WPE in ground observations.

Climatic variables were also significant contributors, with cooler, drier areas exhibiting greater WPE. A likely explanation is that many shrub and cactus species of concern in the study area developed adaptations to desert environments (Chávez-Moreno, Tecante, and Casas 2009), where precipitation is rare and low vapor pressure increases evapotranspiration potential (Zhou et al. 2014).

Though satellite-based remote sensing was immensely beneficial in its ability to provide both data for the entire study area as well as a time-series change analysis, the method was limiting in other ways. The 30m resolution was coarse in comparison to the 2cm resolution of UAS imagery. While individual shrubs were visible in UAS imagery, forest or shrubland pixels in NLCD were generalizations comprised of mosaics of smaller patches of herbaceous, bare, and shrub land cover. For example, Xian et al. (2015) found that on average, just 27% of a given NLCD shrubland pixel was comprised of shrubs. Because of this, shrub cover estimates provided by NLCD are likely dramatically inflated. The weak relationship between UAS- and NLCD-derived shrub cover in the present study supports this. However, while there are undoubtedly differences in the results of two approaches to remote sensing, one is not necessarily better than the other. Each seeks to answer a different question and illustrates the trade-off between spatial resolution and spatial extent (Goodchild 2011). As UAS becomes more commonly used in LSS, its role as a bridge between finer and coarser scales of analysis will emerge.

An LSS Approach to Changing Vegetation Communities

At the heart of Land System Science is the use of mixed methods to interrogate complex questions from a variety of angles. While the vast majority of research on changing plant communities and land degradation has been conducted by rangeland managers, biologists, or remote sensors, this thesis represents a more robust analysis that synthesizes the findings of multiple scales and methods of investigation. However, interpreting the findings of a mixed methods analysis can be complicated by confounding results and an abundance of data addressing multiple interconnected facets of the research topic. For the subject of changing vegetation communities in Union and Cimarron Counties, however, each method provided a unique perspective that helped to more completely answer the research question than if a single approach were used.

By using household surveys as a foundation for subsequent analysis, this investigation captured the perspective of those who have the most intimate knowledge of the land being studied, and who are most directly affected by the plant communities on the land that supports their livelihoods. Though research with human subjects can be error prone (Muchnik, Aral, and Taylor 2013; Stephens-Davidowitz 2017), household surveys revealed that land use and management have a major impact on vegetation. Data provided by landowners showed that herbicide applications are effective at reducing the severity of nuisance trees and shrubs. Additionally, CRP may have unintended effects on biodiversity, especially considering that landowners were more likely to perceive CRP lands as “Encroached”. Further, observations made at the household level effectively scaled up to land-cover data obtained from UAS.

Biodiversity data collected through ground observations also played an important role in providing context for observations at different scales. Neither UAS imagery nor NLCD data could identify herbaceous vegetation to species level, making ground-level observations were the only method to directly evaluate inter-species interactions. However, quantification of woody species and bare ground cover was arguably more effectively measured through UAS observations. The improved spatial extent provided by UAS yielded additional species observations and gave a more representative sample of patterns across entire pastures. This considered, the use of multiple methods to measure the same phenomenon helps to validate the quality of data and ensure consistent results.

UAS imagery classification provided a highly accurate and spatially explicit illustration of vegetation patterns and land degradation, at a scale relevant to land managers. This ultra-high resolution imagery was arguably the most accurate method of measuring the extent and severity of WPE, though certainly lacked detail provided by finer-scale analyses and the spatial extent provided by NLCD data. UAS data, as a moderate-level analysis, was easily linked to survey data to reveal land management trends, demonstrated high levels of agreement with ground observations, and provided finer details than coarser remote sensing. Despite these benefits, the method required significant time to produce usable classified orthophotos.

As the broadest scale of analysis, NLCD regression revealed that climate, soil, and terrain undeniably play a role in WPE severity. This method was advantageous in its ability to measure change over time, while other methods represented conditions only in the summer of 2018. However, the major jump in scale caused some dissonance between NLCD findings and observations made at finer scales. For example, county-level observations in ground- and UAS-based data suggested that WPE was more severe in Cimarron County, while NLCD data showed the opposite. All things considered, each method represented in this thesis carries its own strengths and weaknesses, with each revealing a different perspective on the analysis.

Ultimately, an evaluation of the efficacy of a mixed methods approach must address whether the study questions were answered. As the next chapter continues, the findings of this thesis are presented on a question-by-question basis, to conclusively answer the questions set at the beginning of the project. Additionally, Chapter 5 discusses the scope and limitations of the research and its broader impacts for Land System Science and studies in vegetation change.

CHAPTER V

CONCLUSION

In light of climate change, desertification, increasing economic pressures, and reductions in global biodiversity, the importance of research in the socio-ecological resilience of agricultural communities in drylands has become increasingly amplified. This thesis implemented a Land System Science approach to investigating the causes and consequences of land degradation in rangelands of Union a County, New Mexico and Cimarron County, Oklahoma. Through the synthesis of multiple avenues of investigation, this study concludes that woody plant encroachment is affected by both environmental and land management factors, that it is associated with greater herbaceous plant biodiversity, and that UAS imagery can provide much of the same data obtained through ground observations, though with greater detail and across larger spatial extents.

Interpreting the results of this type of investigation can be complex, particularly when mixed methods are implemented (Bryman 2006) and when multiple spatial scales are analyzed (Wiens 1989). As this thesis concludes, each of the three research questions are addressed.

1) How does woody plant encroachment vary across different environmental gradients, varying land-use/management practices, and sociopolitical boundaries?

To first address the environmental aspect of the question, regression of NLCD change in woody vegetation from 1992-2016 indicated that WPE was positively associated most strongly with terrain ruggedness, possibly because terrain features trap precipitation and increase soil moisture in ways that disproportionately benefit woody vegetation (Wu and Archer 2005). Similarly, sandy soils were also positively associated with WPE, likely for similar reasons. Further, WPE was greatest in areas of more desert-like climate. This suggests that species like cholla and yucca, which are adapted to drier climates with lower vapor pressure, have an evolutionary advantage over herbaceous vegetation in these areas.

Land use and management also played a significant role in vegetation composition. Woody vegetation was more severe on pastures where cattle grazed regularly, while less woody vegetation was observed on lands enrolled in the Conservation Reserve Program. Household surveys revealed that many landowners have taken action to reduce woody vegetation on their land. By linking survey responses to UAS imagery, plots where herbicide was applied were shown to have significantly less woody vegetation than untreated plots. Additionally, landowner perceptions of land quality were largely validated, with "Encroached" plots having more bare soil patches, greater biodiversity, and more woody cover as measured through UAS imagery.

As evidenced by NLCD data, WPE was more severe in Union County, due in part to rugged terrain and sandy soils. However, an ambiguous or contradictory finding was observed at finer scales. Vegetation composition did change across county lines, with greater species richness in Cimarron County. In terms of woody vegetation, broom snakeweed was more common in Union County while yucca was more common in

Cimarron County. However, significant differences in woody vegetation densities were not observed either in UAS imagery or ground-level observations. Land-use/management actions did vary by county, with burning and manual removal more common in Union County, while mowing and CRP were more common in Cimarron County.

Since both environmental and land-use factors play a role in WPE, future research on the topic should examine both in tandem. While certain environmental factors may make land differentially vulnerable to degradation, outcomes appear to be most directly determined by land managers' actions.

2) What is the relationship between herbaceous plant biodiversity and woody plant encroachment? How does it vary across scales?

Complex, nuanced relationships were observed between herbaceous plant biodiversity and woody plant encroachment. It has been observed in other systems that diverse assemblages of grasses and forbs confer stability to help stay woody species invasions. In the present study, weak negative associations between herbaceous and woody species biodiversity were observed. Plots without woody species present had higher herbaceous species biodiversity, on average. Further, bare soil severity was lower in plots with higher herbaceous species biodiversity, suggesting these plots may be less vulnerable to invasions. Future work should more closely examine the relationship between biodiversity and the severity of woody cover, as well as how woody cover increases over time. Further, a closer examination of herbaceous species phenology may help to clarify this relationship.

3) What are the benefits and limitations of multiple scales of analysis, particularly considering the potential role of unmanned aerial systems (UAS) as a scalar bridge in rapid vegetation assessments?

Imagery obtained through UAS was useful in this investigation and served as the benchmark by which other data were evaluated. In some ways, findings of UAS imagery were redundant with ground observations, though UAS imagery was preferable because of its spatially explicit data and larger spatial extent. However, ground observations were advantageous in providing data on herbaceous species. While UAS observations could potentially be used to measure herbaceous vegetation, this study focused exclusively on using UAS to identify woody vegetation to species level.

While satellite remote sensing provided continuous data on the entire study area and illustrated change over time, the resolution was too coarse to effectively link “people to pixels”. The 30m resolution of NLCD data caused some ambiguity in measuring shrub coverage when scaling down to the plot level, and was only weakly associated with the results of UAS imagery. While the ultra-high resolution of UAS imagery allowed analysis of individual trees and shrubs in a spatially explicit manner, satellite remote sensing was better suited to measuring broader patterns.

Because LSS seeks, in part, to connect “people to pixels,” UAS should be more broadly used in LSS investigations because of its ability to more accurately compare fine-scale land-use actions with remotely sensed land-cover data.

Scope and Limitations

While each method implemented in this thesis carries its own benefits and shortcomings, the overall study design, as with all research, has limitations. Perhaps most notably, the LSS approach emphasizes breadth over depth. While the mixed methods approach certainly helped to construct a more complete illustration of the dynamic causes of vegetation change, time was ultimately a limiting factor. As a result, vegetation sampling used rapid assessment protocols, and satellite remote sensing utilized NLCD, a product with documented limitations (Wickham et al. 2004). Additionally, while direct comparison of 2016 NLCD to 2018 field and UAS observations was useful as a demonstration of scalar linkages, the researchers acknowledge some changes in vegetation occurred during this two-year period. All things considered, the present investigation offers less detail into specific phenomenon such as temporal changes in herbaceous vegetation (e.g., Jurena and Archer 2003) or the biogeochemical processes behind fire suppression (e.g., Biggs 1997), but a more diverse breadth of analyses to help untangle how these factors might interact synergistically.

Small sample sizes were another limitation encountered when employing multiple modalities with finite time and resources. This investigation studied 20 households and 40 ground/UAS plots, reducing the likelihood of making statistically significant observations. While this sample cannot account for variation across the entire region, the use of jackknife predictive estimates and NLCD observations of the region as a whole help to contextualize small *n* observations.

Sampling methodology or the small sampling size could also be a factor affecting biodiversity findings. Emphasizing the utility of rapid assessments, this study used the

IFRI protocol to quickly examine biodiversity in small areas, at a single snapshot in time. Most of the species observed during sampling were perennial, warm-season species. Cool-season species may not have been captured in surveys and the temporal stability conferred through greater biodiversity (Zemunik et al. 2016) may not be represented in the dataset. Further, spatial heterogeneity in grasslands can be difficult to capture in a single plot (Parker et al. 2011). Despite this, the adaptation of IFRI methods for grasslands was useful as a rapid assessment approach, and the nested plot design was effective for comparison to UAS observations.

In terms of UAS classification, high resolution and modern classification methods helped to produce a highly accurate land-cover product. This considered, a discrete classification has its limitations in measuring, for example, the quality of grass cover, even at such a high resolution. As research in UAS imagery classification progresses, exploration into continuous classifications that might capture these gradients will be necessary to more effectively capture pattern-process relationships (Cushman et al. 2010). Additionally, while the scope of this investigation primarily utilized UAS imagery as a direct comparison to other scales and methods of observation, numerous other potential uses for the UAS dataset exist, such as studying fine-scale spatial patterns of shrub distributions, detecting possible allelopathic relationships between species, and examining microhabitats provided by terrain features.

Future Directions

Considering the limitations of collecting data during a single snapshot in time, particularly in such a dynamic use case, UAS flights will be repeated five years from their original date to examine how the landscape changes over time. Acquiring a time series dataset through UAS is imperative to fully evaluating the role of the novel technology in land change studies, and LSS more broadly. Further, this repeat photography project will allow a more direct comparison to vegetation change measured through satellite remote sensing. Additionally, measuring change over time will more directly address questions of which land management methods are most effective in reducing woody vegetation; several research participants will be conducting prescribed burns during the intervening five years, providing more data on that management method.

The potential for detection of herbaceous vegetation through UAS is promising, particularly considering the emergence of hyperspectral sensors that can identify certain wavelengths of light associated with particular species (Sankey et al. 2017). To more effectively evaluate the role of UAS as a "bridge," further exploration into its possible use measuring herbaceous biodiversity in rangelands is merited. Additionally, research on herbaceous vegetation could help measure ranchers' species of greatest concern, such as locoweed, as well as herbaceous weeds of concern for farmers.

Structure-from-motion height data obtained through UAS flights also has promising applications including volumetric analysis of above-ground biomass (Carrivick 2016; Gillan et al. 2014) or modeling of species growth potential and fine-scale distribution patterns (Mairota et al. 2014). Future analyses can make use of these data to help rangeland managers more effectively make decisions and ensure the long-term sustainability of their lands.

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APPENDICES

APPENDIX A: Institutional Review Board Approval

Oklahoma State University Institutional Review Board

Date:	05/18/2018
Application Number:	AS-18-24
Proposal Title:	Participatory Approaches to Agroecosystem Resilience in Time of Drought (ARID): An Example from the Southern Great Plains
Principal Investigator:	Jacqueline Vadjunec
Co-Investigator(s):	Kate Zeigler, Todd Fagin
Faculty Adviser:	
Project Coordinator:	Amy Ganguli
Research Assistant(s):	Austin Boardman, Fernanda Ramirez Saenz, Maria Sol Ramirez Saenz
Processed as:	Expedited

Status Recommended by Reviewer(s): Approved
Approval Date: **05/17/2018**
Expiration Date: **05/16/2019**

The IRB application referenced above has been approved. It is the judgment of the reviewers that the rights and welfare of individuals who may be asked to participate in this study will be respected, and that the research will be conducted in a manner consistent with the IRB requirements as outlined in section 45 CFR 46.

The final versions of any recruitment, consent and assent documents bearing the IRB approval stamp are available for download from IRBManager. These are the versions that must be used during the study.

As Principal Investigator, it is your responsibility to do the following:

1. Conduct this study exactly as it has been approved. Any modifications to the research protocol must be approved by the IRB. Protocol modifications requiring approval may include changes to the title, PI, adviser, other research personnel, funding status or sponsor, subject population composition or size, recruitment, inclusion/exclusion criteria, research site, research procedures and consent/assent process or forms.
2. Submit a request for continuation if the study extends beyond the approval period. This continuation must receive IRB review and approval before the research can continue.
3. Report any unanticipated and/or adverse events to the IRB Office promptly.
4. Notify the IRB office when your research project is complete or when you are no longer affiliated with Oklahoma State University.

Please note that approved protocols are subject to monitoring by the IRB and that the IRB office has the authority to inspect research records associated with this protocol at any time. If you have questions about the IRB procedures or need any assistance from the Board, please contact the IRB Office at 223 Scott Hall (phone: 405-744-3377, irb@okstate.edu).

Sincerely,

Hugh Crethar, Chair Institutional Review Board

CITI PROGRAM

Completion Date 06-May-2018
Expiration Date 05-May-2021
Record ID 27020314

This is to certify that:

Austin Boardman

Has completed the following CITI Program course:

Human Subjects - Specialized Courses	(Curriculum Group)
Community Based Participatory Research Procedures	(Course Learner Group)
1 - Basic	(Stage)

Under requirements set by:

Oklahoma State University

CITI
Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?w7e2b9e48-8951-4c55-a476-0d02b6a08981-27020314

APPENDIX B: Relevant Household Survey Questions

Do you have any of the following land management issues on your property? (check all that apply, and rate severity, where 1 is least severe and 5 is most severe)

☐ Cholla Cactus 1 2 3 4 5 ☐ Mesquite 1 2 3 4 5
☐ Juniper 1 2 3 4 5 ☐ Salt Cedar 1 2 3 4 5
☐ Other woody plant: 1 2 3 4 5 List:_________________________
☐ Insect/pest issues 1 2 3 4 5 List:_________________________
☐ Prairie Dogs 1 2 3 4 5 ☐ Yucca 1 2 3 4 5
☐ Russian Thistle 1 2 3 4 5 ☐ Bindweed 1 2 3 4 5
☐ Loco weed 1 2 3 4 5 ☐ Other weed 1 2 3 4 5 List:__________
☐ Soil Erosion 1 2 3 4 5 ☐ Soil compaction 1 2 3 4 5
☐ Grass degradation or die back 1 2 3 4 5
☐ Other (specify). Explain:____

On a scale of 1-5 (1 being low, 5 being high), how much effort have you put into removing invasive and nuisance (e.g. unwanted) plants/species from your land? 1 2 3 4 5

Which of the following methods have you used to reduce invasive or unwanted plants on your land?

☐ Controlled burning (Frequency? ___________)
☐ Manual removal or mechanical control (saw, loppers, skid steer, backhoe, masticator, chaining etc.) (Explain:_____________________________ Frequency? ___________)
☐ Mowing (Frequency? ___________)
☐ Herbicide (Frequency? ___________)
☐ Biological (insect) control (Explain:________________________________Frequency? ___________)
☐ Changing grazing patterns (Explain: _____________________________ _Frequency? ___________)
☐ Other: ____

Which of the following methods have you used to improve soil productivity on your land? Explain.

☐ Controlled burning___________ ☐Cover crops:___________________ ☐ Fertilizer:_____________
☐ Rotational grazing:(Explain rotation)____
____
____
☐ Please list any other methods used (discuss): ____
____
____

APPENDIX C: UAS Plot Land Management Questionnaire

PLOT 1 (with nuisance species)

☐ PRIVATELY OWNED ☐ STATE ☐ FEDERAL

If leased, what year did your lease begin? _________

	CULTIVATED (SPECIFY CROP)	GRAZED (ESTIMATE # CATTLE)	CONSERVATION RESERVE PROGRAM	BURNED	MOWED	HERBICIDE APPLIED TO REDUCE TREES/SHRUBS	MANUAL TREE/SHRUB REMOVAL	OTHER
2009								
2010								
2011								
2012								
2013								
2014								
2015								
2016								
2017								
2018								

PLOT 2

(without nuisance species)

☐ PRIVATELY OWNED ☐ STATE ☐ FEDERAL

If leased, what year did your lease begin? _________

	CULTIVATED (SPECIFY CROP)	GRAZED (ESTIMATE # CATTLE)	CONSERVATION RESERVE PROGRAM	BURNED	MOWED	HERBICIDE APPLIED TO REDUCE	MANUAL TREE/SHRUB REMOVAL	OTHER
2009								
2010								
2011								
2012								
2013								
2014								
2015								
2016								
2017								
2018								

APPENDIX D: Point Cloud Processing Python Script

```
import arcpy
print("imported arcpy")

if arcpy.CheckExtension("3D") == "Available":
    arcpy.CheckOutExtension("3D")
else:
    # raise a custom exception
    print("LicenseError1")

if arcpy.CheckExtension("Spatial") == "Available":
    arcpy.CheckOutExtension("Spatial")
else:
    # raise a custom exception
    print("LicenseError2")

arcpy.env.workspace = r"G:\Thesis\Classification.gdb"
print("workspace set")
scratch = r"G:\Thesis\Scratch" "\\"
raw = r"G:\Thesis\Raw" "\\"
plotList = ["a010202_1", "a010202_2", "a010502_1", "a010502_2",
"a010801_1",\
  "a010801_2", "a011002_1", "a011002_2", "a011602_1", "a011602_2",\
  "a012002_1", "a012002_2", "a012101_1", "a012101_2", "a012502_1",\
  "a012502_2", "a012803_1", "a012803_2", "a013002_1", "a013002_2",\
  "a020002_1", "a020002_2", "a020103_1", "a020103_2", "a020302_1",\
  "a020302_2", "a020702_1", "a020702_2", "a021302_1", "a021302_2",\
  "a021402_1", "a021402_2", "a022103_1", "a022103_2", "a022802_1",\
  "a022802_2", "a023002_1", "a023002_2", "a023302_1", "a023302_2"]

for currentPlot in plotList:
    print("The current plot is "+currentPlot)
    currentLas = raw+currentPlot+".las"
    print("LAS file found in directory "+currentLas)
    print("vars defined")
    arcpy.conversion.LasDatasetToRaster(currentLas,
currentPlot+"_dsm",\
      "ELEVATION", "BINNING AVERAGE LINEAR", "FLOAT", "CELLSIZE", 0.02,
1)
    print("dsm generated")
    #
    arcpy.ddd.ClassifyLasGround(currentLas, "CONSERVATIVE",\
      "RECLASSIFY_GROUND", "0.3 Unknown", "NO_COMPUTE_STATS",
"DEFAULT",\
      None, "PROCESS_EXTENT")
    print("classification completed")
    #
    arcpy.management.MakeLasDatasetLayer(currentLas,\
      scratch+currentPlot+"_laslyr", "2")
```

```
    print("ground las layer generated, saved as\
      "+scratch+currentPlot+"_laslyr")
    arcpy.conversion.LasDatasetToRaster(scratch+currentPlot+"_laslyr",\
      currentPlot+"_dtm", "ELEVATION", "BINNING AVERAGE LINEAR",
"FLOAT",\
      "CELLSIZE", 0.02, 1)
    print("dtm generated")
    dsm=currentPlot+"_dsm"
    dtm =currentPlot+"_dtm"

    from arcpy.sa import *
    nDSM = Raster(dsm)-Raster(dtm)
    arcpy.CopyRaster_management(nDSM,currentPlot+"_ndsm")
    print("raster calculator completed, ndsm generated")

    currentPlotTif = rawfs+currentPlot+".tif"
    currentPlotnDSM = currentPlot+"_ndsm"
    compIn = "'"+currentPlotTif+"';'"+currentPlotnDSM+"'"
    print(compIn)
    arcpy.CompositeBands_management(compIn,currentPlot + "_rgbh")

arcpy.CheckInExtension("3D")
arcpy.CheckInExtension("Spatial")
print("Geoprocessing complete.")
```

APPENDIX E: UAS Classification Accuracy Assessment

Plot ID	Total Accuracy	Kappa	User's Accuracy											Producer's Accuracy										
			Bare	Grass	Snake-weed	Yucca	Sage	Clover	Cholla	Juniper	Mesquite	Water	Cotton-wood	Bare	Grass	Snake-Weed	Yucca	Sage	Clover	Cholla	Juniper	Mesquite	Water	Cotton-wood
1	97.2%	0.907	100%	100%	70%	—	—	—	—	—	—	—	—	100%	97%	100%	—	—	—	—	—	—	—	—
2	90.8%	0.648	40%	98%	100%	30%	—	—	—	—	—	—	—	57%	92%	100%	100%	—	—	—	—	—	—	—
3	88.5%	0.580	50%	98%	—	—	50%	—	—	—	—	—	—	100%	89%	—	—	71%	—	—	—	—	—	—
4	91.5%	0.779	100%	90%	—	—	100%	—	—	—	—	—	—	83%	100%	—	—	59%	—	—	—	—	—	—
5	95.4%	0.855	80%	97%	100%	—	—	—	—	—	—	—	—	80%	98%	91%	—	—	—	—	—	—	—	—
6	91.3%	0.790	60%	96%	100%	—	—	70%	—	—	—	—	—	100%	93%	83%	—	—	78%	—	—	—	—	—
7	89.8%	0.716	90%	92%	—	70%	—	—	—	—	—	—	—	64%	95%	—	88%	—	—	—	—	—	—	—
8	81.3%	0.707	66%	94%	—	50%	—	—	—	36%	—	—	97%	89%	80%	—	71%	—	—	—	80%	—	—	81%
9	82.1%	0.695	94%	89%	—	50%	93%	—	—	—	—	—	—	68%	85%	—	94%	76%	—	—	—	—	—	—
10	88.5%	0.580	80%	98%	—	20%	—	—	—	—	—	—	—	89%	89%	—	67%	—	—	—	—	—	—	—
11	89.9%	0.725	70%	98%	60%	50%	—	—	70%	—	—	—	—	78%	92%	100%	56%	—	—	100%	—	—	—	—
12	88.8%	0.719	77%	99%	50%	68%	—	—	8%	100%	—	—	—	100%	88%	83%	94%	—	—	100%	91%	—	—	—
13	82.2%	0.629	75%	96%	—	36%	—	—	—	—	—	—	—	88%	79%	—	100%	—	—	—	—	—	—	—
14	81.3%	0.567	79%	100%	—	22%	—	—	—	—	—	—	—	100%	78%	—	100%	—	—	—	—	—	—	—
15	81.3%	0.697	79%	72%	—	—	—	—	—	100%	—	—	—	84%	64%	—	—	—	—	—	100%	—	—	—
16	91.5%	0.722	70%	95%	70%	—	—	—	—	80%	—	—	—	50%	96%	88%	—	—	—	—	89%	—	—	—
17	85.8%	0.554	71%	95%	20%	—	—	—	50%	—	—	—	—	60%	89%	100%	—	—	—	100%	—	—	—	—
18	88.4%	0.603	27%	100%	—	—	—	—	70%	—	—	—	—	100%	87%	—	—	—	—	100%	—	—	—	—
19	86.2%	0.701	36%	92%	—	—	—	—	70%	86%	—	—	—	50%	91%	—	—	—	—	—	100%	76%	—	—
20	85.1%	0.581	50%	91%	—	—	—	—	60%	69%	—	—	—	36%	91%	—	—	—	—	—	100%	69%	—	—
21	94.4%	0.810	100%	99%	—	50%	—	—	—	—	—	—	—	91%	95%	—	100%	—	—	—	—	—	—	—
22	89.1%	0.583	70%	97%	60%	20%	—	—	—	—	—	—	—	58%	93%	75%	67%	—	—	—	—	—	—	—
23	90.8%	0.741	75%	98%	—	40%	—	—	80%	60%	—	—	—	89%	92%	—	80%	—	—	80%	75%	—	—	—
24	93.8%	0.770	50%	100%	—	—	—	—	—	80%	—	70%	—	100%	93%	—	—	—	—	—	100%	—	100%	—
25	84.3%	0.753	59%	95%	—	—	—	—	—	100%	—	—	—	89%	77%	—	—	—	—	—	95%	—	—	—
26	88.4%	0.722	100%	91%	—	30%	—	—	—	100%	—	—	—	61%	98%	—	50%	—	—	—	71%	—	—	—
27	90.7%	0.715	100%	93%	100%	30%	—	—	—	—	—	—	—	63%	99%	53%	100%	—	—	—	—	—	—	—
28	91.6%	0.735	82%	98%	100%	10%	—	—	—	—	—	—	—	100%	94%	71%	100%	—	—	—	—	—	—	—
29	88.5%	0.806	97%	93%	50%	29%	96%	—	—	—	—	—	—	82%	93%	50%	80%	88%	—	—	—	—	—	—
30	89.7%	0.674	50%	97%	50%	20%	89%	—	—	—	—	—	—	63%	95%	83%	50%	63%	—	—	—	—	—	—

Plot ID	Total Accuracy	Kappa	User's Accuracy											Producer's Accuracy										
			Bare	Grass	Snake-weed	Yucca	Sage	Clover	Cholla	Juniper	Mesquite	Water	Cotton-wood	Bare	Grass	Snake-Weed	Yucca	Sage	Clover	Cholla	Juniper	Mesquite	Water	Cotton-wood
31	89.4%	0.641	50%	97%	50%	—	—	—	—	—	—	—	—	71%	91%	88%	—	—	—	—	—	—	—	—
32	89.5%	0.714	85%	96%	50%	—	—	—	—	—	—	—	—	92%	91%	71%	—	—	—	—	—	—	—	—
33	89.5%	0.725	73%	92%	90%	—	—	—	—	—	—	—	—	57%	94%	100%	—	—	—	—	—	—	—	—
34	94.1%	0.808	70%	99%	80%	—	—	—	—	—	—	—	—	100%	94%	89%	—	—	—	—	—	—	—	—
35	97.1%	0.906	70%	100%	100%	—	—	—	—	—	—	—	—	100%	96%	100%	—	—	—	—	—	—	—	—
36	96.2%	0.884	80%	98%	100%	—	—	—	—	—	—	—	—	100%	98%	83%	—	—	—	—	—	—	—	—
37	87.5%	0.733	40%	92%	95%	—	—	—	—	—	—	—	—	67%	90%	87%	—	—	—	—	—	—	—	—
38	91.6%	0.754	90%	93%	80%	—	—	—	—	—	—	—	—	75%	96%	73%	—	—	—	—	—	—	—	—
39	81.7%	0.519	64%	89%	—	10%	—	—	—	67%	60%	—	—	41%	91%	—	100%	—	—	—	67%	55%	—	—
40	80.7%	0.626	76%	88%	—	—	—	—	—	64%	56%	—	—	67%	85%	—	—	—	—	—	78%	82%	—	—
Average	**88.9%**	**0.709**	**72%**	**95%**	**75%**	**35%**	**86%**	**70%**	**58%**	**78%**	**58%**	**70%**	**97%**	**79%**	**91%**	**84%**	**83%**	**72%**	**78%**	**96%**	**87%**	**70%**	**100%**	**81%**
St. Dev.	**4.5%**	**0.095**	**19%**	**5%**	**24%**	**17%**	**18%**	**0%**	**22%**	**19%**	**2%**	**0%**	**0%**	**19%**	**7%**	**14%**	**18%**	**10%**	**0%**	**8%**	**12%**	**10%**	**0%**	**0%**

APPENDIX F: List of Plant Species in Ground Observations

Family	Scientific Name	Common Name	# of Plots Present
Agavaceae	*Yucca glauca*	Great Plains yucca	7
Amaranthaceae	*Amaranthus arenicola*	Sandhills pigweed	1
Amaranthaceae	*Kali tragus*	Russian thistle	2
Amaranthaceae	*Kochia scoparia*	Kochia	1
Anacardiaceae	*Rhus aromatica*	Fragrant sumac	1
Asteraceaae	*Ambrosia psilostachya*	Western ragweed	8
Asteraceae	*Artemisia filifolia*	Sand sage	4
Asteraceae	*Cirsium ochrocentrum*	Yellow spine thistle	1
Asteraceae	*Conyza canadensis*	Horseweed	2
Asteraceae	*Dyssodia papposa*	Fetid marigold	7
Asteraceae	*Erigeron modestus*	Plains fleabane	3
Asteraceae	*Gutierrezia sarothrae*	Broom snakeweed	17
Asteraceae	*Leucelene ericoides*	White aster	1
Asteraceae	*Lygodesmia juncea*	Skeletonweed	1
Asteraceae	*Machaeranthera tanacetifolia*	Tansy aster	1
Asteraceae	*Ratibida tagees*	Shortray prairie coneflower	2
Asteraceae	*Thelesperma filifolim*	Greenthread	1
Asteraceae	*Zinnia grandiflora*	Rocky Mountain zinnia	1
Boraginaceae	*Cryptantha minima*	Little cryptantha	1
Brassicaceae	*Descurainia sophia*	Tansy mustard	1
Cactaceae	*Cylindropuntia imbricata*	Walking stick cholla	8
Cactaceae	*Escobaria missouriensis*	Missouri foxtail cactus	1
Cactaceae	*Opuntia phaeacantha*	Prickly pear	7
Cannabaceae	*Celtis reticulata*	Western hackberry	1
Chenopodiaceae	*Chenopodium simplex*	Maple-leaved goosefoot	1
Convolvulaceae	*Convolvulus arvensis*	Field bindweed	2
Cupressaceae	*Juniperus monosperma*	One-seed juniper	3
Euphorbiaceae	*Euphorbia prostrata*	Prostrate sandmat	1
Fabaceae	*Caesalpina jamesii*	James' rush-pea	3
Fabaceae	*Dalea candida*	White prairie clover	1

Family	Scientific Name	Common Name	# of Plots Present
Fabaceae	*Dalea enneandra*	9-anther prairie clover	1
Fabaceae	*Dalea jamesii*	James' prairie clover	1
Fabaceae	*Dalea tennuifolium*	Slim-leaf prairie clover	1
Fabaceae	*Melilotus officinalis*	Yellow clover	2
Fabaceae	*Oxytropis lambertii*	Purple locoweed	1
Fabaceae	*Prosopis glandulosa*	Honey mesquite	3
Fabaceae	*Psoralea tenuiflora*	Wild alfalfa	5
Fabaceae	*Sophora nuttaliana*	White locoweed	3
Onagraceae	*Gaura villosa*	Hairy gaura	1
Pinaceae	*Pinus edulis*	Pinyon pine	1
Plantaginaceae	*Plantago patagonica*	Wooly plantain	10
Poaceae	*Aristida purpurea*	Purple threeawns	3
Poaceae	*Bothriochloa bladhii*	Old world bluestem	3
Poaceae	*Bouteloua curtipendula*	Sideoats grama	4
Poaceae	*Bouteloua gracillis*	Blue grama	15
Poaceae	*Bouteloua hirsuta*	Hairy grama	8
Poaceae	*Buchloe dactyloides*	Buffalograss	23
Poaceae	*Chloris verticillata*	Windmillgrass	1
Poaceae	*Panicum obtusum*	Vine mesquite	1
Poaceae	*Pascopyrum smithii*	Western wheatgrass	1
Poaceae	*Sitanion hystrix*	Squirreltail	2
Poaceae	*Stipa comata*	Needle-and-thread	2
Poaceae	*Vulpia octoflora*	Sixweeks fescue	2
Salicaceae	*Populus deltoides*	Eastern cottonwood	1
Ulmaceae	*Ulmus pumila*	Siberian elm	1

VITA

Austin L. Boardman

Candidate for the Degree of

Master of Science

Thesis: THE NEXT GENERATION OF LAND SYSTEM SCIENCE: INTEGRATING MESO-SCALE ANALYSIS AND UAS REMOTE SENSING IN CHANGING PLANT COMMUNITIES OF THE UNITED STATES' SOUTHERN GREAT PLAINS

Major Field: Geography

Biographical:

Education:

Completed the requirements for the Master of Science in Geography at Oklahoma State University, Stillwater, Oklahoma in May, 2020.

Completed the requirements for Bachelor of Science in Biological Sciences at the University of Tulsa, Tulsa, Oklahoma in 2014.

Experience:

Biological Science Technician, Yosemite National Park, Yosemite, CA (May 2015 – November 2019, Seasonal)

Research Assistant, Oklahoma State University, Stillwater, OK (January 2018 – May 2019)

Business Analyst, Skin Care Institute, Tulsa, OK (October 2015 – May 2019)

Cartographic Technician, Oklahoma State University, Stillwater, OK (January 2017 – May 2017)

Professional Memberships:

American Association of Geographers