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Examining Columbian Sharp-tailed Grouse Nesting and Brood Rearing Habitat Using Machine Learning and Land Use and Land Cover Trends in Southeastern Idaho

By

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A thesis submitted in partial fulfillment of the requirements for the degree of

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Dedication

I dedicate this to my wife, for encouraging me to do things despite my internal fears. I could not have done this without her support.

For the rest of my family, and all their support over the years. Every journey has its ups and downs, but I remember where I came from and I'm finally getting where I wanted to go.

For my friends. Friends are the family that you choose. Thanks for listening to me ramble about ground control points and ground birds for the last few years.

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List of Abbreviations/Symbols

AICc	Corrected Akaike Information Criteria
CSTG	Columbian Sharp-tailed Grouse
CRP	Conservation Reserve Program
GCP	Ground Control Point
GEM3	Genes by Environment, Mapping, Mechanisms, and Modeling
GNSS	Global Navigation Satellite System
GWR	Geographically Weighted Regression
IDFG	Idaho Department of Fish and Game
LULC	Land Use and Land Cover
NLCD	National Land Cover Dataset
MRLCC	Multi-Resolution Land Characteristics Consortium
MRDCS	Micasense Rededge Dual Camera System
RF	Random Forest
RSC	Rangeland Shrub Component
SLE	Scan Line Error
SVM	Support Vector Machine
UAS	Uncrewed Aircraft System
UgCS	Universal Ground Control Software

Examining Columbian Sharp-tailed Grouse Nesting and Brood Rearing Habitat Using Machine Learning and Land Use and Land Cover Trends in Southeastern Idaho

Thesis Abstract -- Idaho State University (2022)

This project found a relationship between Columbian Sharp-tailed Grouse lek counts and the rate of change in land cover types and burned area within 4 kilometers of a lek between 1985 and 2018. A mitigating factor is the presence of Conservation Reserve Program (CRP) within that nesting and brood rearing habitat. Geographically Weighted Regression analysis indicates reduced lek counts in areas with increased fire area ($r^2 = 0.944$), decreased sagebrush cover ($r^2 = 0.949$), and low CRP area ($r^2 = 0.957$). Additionally, we surveyed a wildfire impacted CRP field using Uncrewed Aerial Systems (UAS) to create a high-resolution vegetation classification map to compare with Sentinel-2 multispectral imagery. Support Vector Machines resulted in the best classification accuracy across two study fields using UAS (0.798, 0.893) and sentinel (0.454, 0.439). The UAS habitat survey revealed increased cheatgrass and decreased sage and shrub cover in burned areas (+14.4% annuals, -12.6% perennials and shrubs).

Keywords: Columbian Sharp-tailed Grouse, habitat mapping, classification, Support Vector Machines, Rangeland Shrub Component, wildfire, wildland fire, UAS, Sentinel-2, multispectral, photogrammetry, remote sensing, Conservation Reserve Program, Geographically Weighted Regression

Chapter 1. Introduction

1.1 Background

The sagebrush-steppe ecosystem of the Western United States supports a diverse community of plant and animal species (Davies et al., 2011). Currently, the sagebrush-steppe is under threat from several anthropogenic pressures. Anthropogenic climate change generally contributes to warmer and drier conditions and increasing average wind speed (Fried et al., 2004). Studies from Idaho National Lab show a decrease in windspeeds during the spring and mixed higher and lower windspeeds during the summer (Buotte et al., 2014). Windspeed has direct impact on the size and frequency of wildfires in the western United States (Murphy et al., 2018; Prudencio et al., 2018; Weber, 2020). Fires negatively affect land cover (Noson et al., 2006) leading to the spread of invasive plant species such as Cheatgrass (*Bromus tectorum*) and reduce habitat quality (Bradley et al., 2018). Further, fire impacts soil quality, leading to soils which have increased erosion as well as debris flows (Meyer and Pierce, 2003, Thomas et al., 2021). Increased development of agriculture and urbanization impacts local species, and causes habitat fragmentation and degradation (Hemstrom et al., 2002). Additionally, human over-predation on wildlife species reduces biodiversity (Connelly et al., 2000). Loss and degradation of habitat space across the Intermountain West has impacted many species of grouse (Swenson et al., 1987). A species that relies on the sagebrush steppe ecosystem is the Columbian Sharp-

Tailed Grouse (CSTG), *Tympanuchus phasianellus columbianus*, and is the smallest subspecies of Sharp-Tailed Grouse (Andersen et al., 2015).

CSTG are endemic to the sagebrush-steppe of western North America, formerly occupying the area from British Columbia to Northern New Mexico, shown in Figure 1 (Andersen et al., 2015). Idaho Department of Fish and Game (IDFG) estimates 60 – 65% of the entire CSTG population resides in Idaho, and because of the reduction in extent, the US Fish and Wildlife agency has been petitioned to add CSTG to the endangered species list, twice, in 1995 and 2004. Ultimately the CSTG has not been added to the list. Subsequently, CSTG has been listed as "critically imperiled" in the Idaho Comprehensive Wildlife Conservation Strategy (Idaho Department of Fish and Game, 2017).

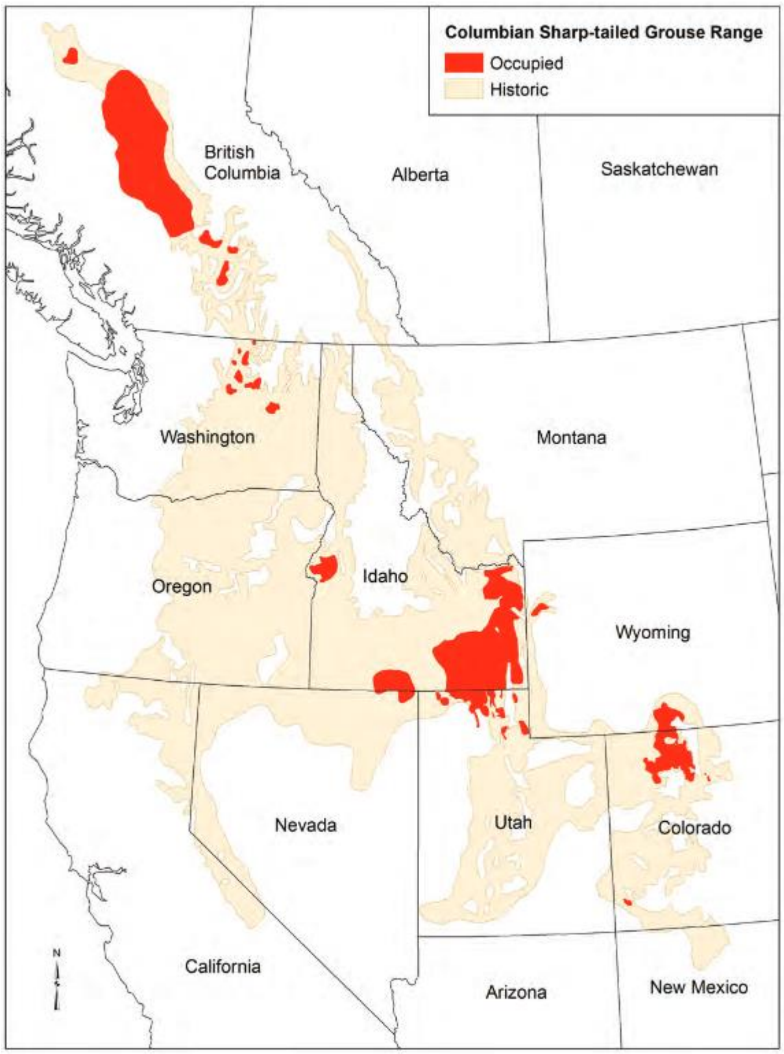

Figure 1. Historic and Current Range of Columbian Sharp-tailed Grouse from Andersen et al., 2015.

In southeastern Idaho the sagebrush steppe includes three species of sagebrush: Big sagebrush (*Artemisia tridentata spp., wyomingensis*), Dwarf sagebrush (*Artemisia arbuscula ssp. thermopola*), and Threetip sagebrush (*Artemisia* *tripartita*); four species of perennial grasses: Fescue-wheatgrass (*Festuca-Agropyron*), Wheatgrass-bluegrass (*Agropyron-Poa*), Mountain Brome (*Bromus marginatus*), and Snake River Wheatgrass (*Elymus wawawaiensis*); and additionally, four species of juniper: Ground Juniper (*Juniperus communis*), Rocky Mountain Juniper (*Juniperus scopulorum*), Utah Juniper (*Juniperus osteosperma*), Western Juniper (*Juniperus occidentalis*). Changes in climate, land use and land cover (LULC), along with wildfire are rapidly altering the characteristics of the sagebrush steppe landscape, and data driven decision making is essential for land managers to respond with appropriate measures. Disentangling which of the changes in LULC, fire regime, and/or climate are most important will allow researchers and land managers to focus time and resources on determining characteristics that are understudied relative to their importance.

To address the loss and fragmentation of habitat and soil cover, the Conservation Reserve Program (CRP) began in 1985 with the passing of the 1985 Farm Bill (Food Security Act of 1985, 1985), and was continued by the Agricultural Improvement Act of 2018 (Robbins, 2014). CRP has specific goals that outline reimbursement policies for farmers for short to medium term restoration of plants to support the local ecology, using beneficial native and nonnative vegetation to maintain soil cover and lower erosion rates (Rodgers and Hoffman, 2005). Southeast Idaho, which is predominatly private land holdings, the CRP provides an important source of land cover for species like the CSTG.

The aim of this research is to understand the CSTG lekking population’s response to changes in LULC in the counties of Bannock, Oneida, and Power in southeast Idaho. This project uses the Multi-Resolution Land Characteristics Consortium’s (MRLCC) Rangeland Shrub Component (RSC) data product (Rigge et al., 2020) to examine the spatio-temporal changes in vegetation at a regional scale in relation to changing population counts recorded at

CSTG leks across southeastern Idaho (n = 318) from 1984-2019 by IDFG. The RSC is a yearly percent cover dataset between 1984-2019 at 30 m resolution and represents several layers: shrub, herbaceous, bare ground, litter, sagebrush, and annual herbaceous land covers. The first objective of this thesis is to determine if the lekking population trend is related to changes in LULC within 4 km of lek sites and if the amount of CRP lands near leks is influencing the population trends. The second objective is a pilot effort to map fine scale CSTG nesting and brooding habitat on 80 ha of CRP lands located within 4 km of a CSTG lekking site. This effort evaluates and provides recommendations for uncrewed aircraft system (UAS) mapping using the Micasense Rededge Dual Camera System multispectral sensor for field scale vegetation and habitat mapping. In addition, this study evaluates the recovery of a CRP study site that was partially burned in 2014, with adjacent unburned area.

1.2 Study Areas

This thesis examines sagebrush-steppe habitat and lekking locations in three counties of southeast Idaho: Bannock, Oneida, and Power. This area is within the northeast ranges of the Great Basin physio geographic region and bordered to the north by the Snake River Plain (Figure

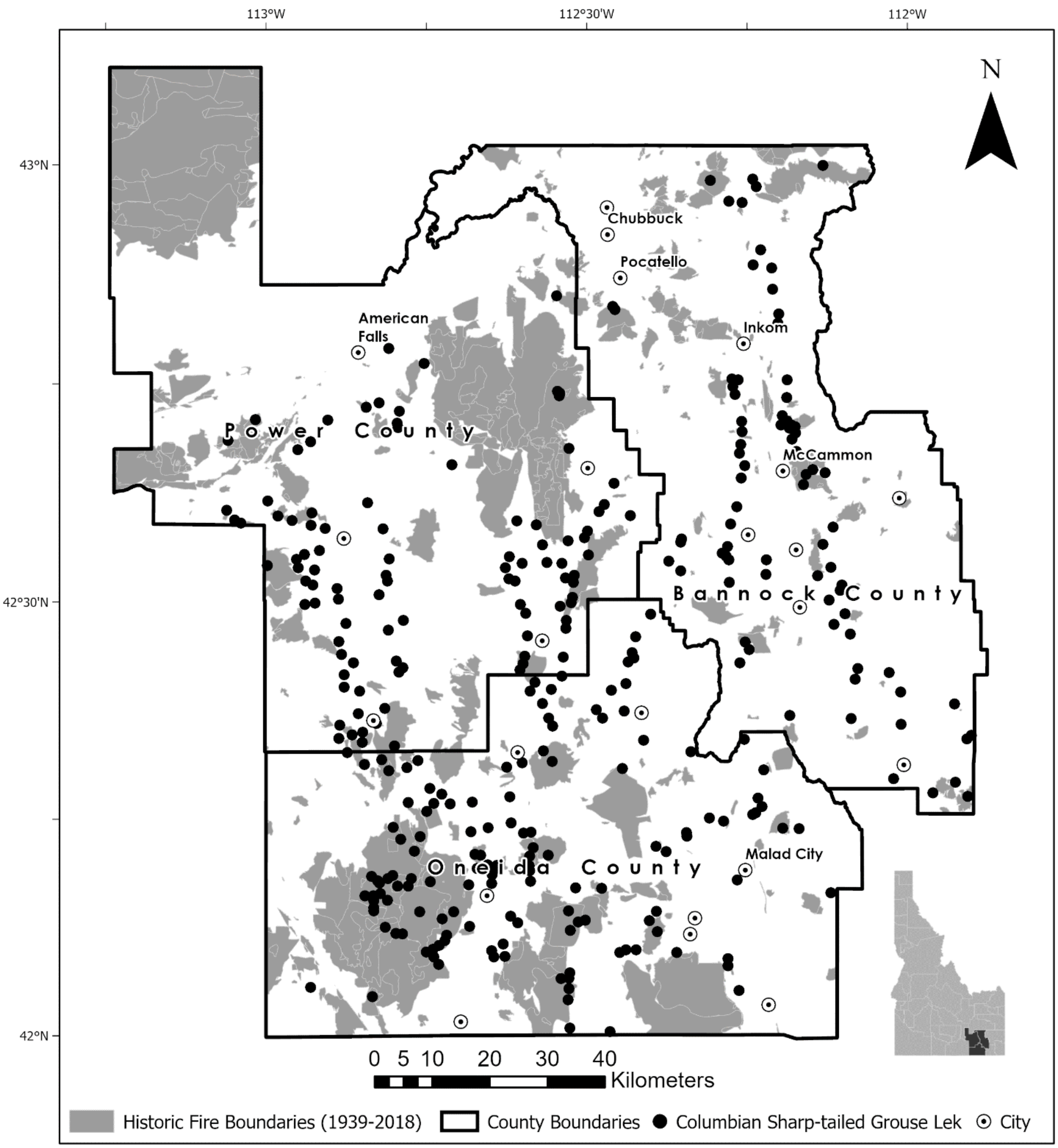

Figure 2. Fire Boundaries and Columbian Sharp-tailed lek locations in Bannock, Power and Oneida counties.

2. Fire Boundaries and Columbian Sharp-tailed lek locations in Bannock, Power and Oneida counties). Chapter 3 examines CRP area and LULC trends over the time range of 1984 to 2019, using the RSC data product (Rigge et al., 2020). This area contains 314 documented CSTG lek sites with mean yearly population counts between 1985 and 2019, that corresponds with the availability of RSC data. Finally, 968 wildfires were recorded for this area between the period from 1939-2018.

The study area for Chapter 4 represents 160 ha of CRP land over two fields, that offers refuge for a nesting and brooding population of CSTG. These fields are located on the eastern side of the marsh valley in central Bannock County, and are part of the northeast extent of the basin and range. These fields fall within the nesting and brood rearing area for three separate leks with mean lek counts between 9 to 14 between 2010 and 2018. Additionally, the Cambridge fire burned 17.5 ha along the northeastern quadrant of this area in 2014 (Figure 3).

1.3 Broader Impacts

This research is partially funded by, contributes to, and builds upon work by researchers in the Genes by Environment, Mapping, Mechanisms, and Modeling (GEM3), Idaho EPSCoR program (NSF Award No. OIA-1757324). The GEM3 program funds scientists who seek to understand how species adapt to external pressures through mapping and modeling the response to the environment, in this case the response in lekking behavior of CSTG to changes in the sagebrush steppe environment. Research outcomes from this project will support other GEM3 projects with the goal of understanding other characteristics of adaptive capacity in the sagebrush steppe environment. Further, our study is conducted in collaboration with IDFG and the United States Department of Agriculture Farm Service Agency Conservation Reserve Program (CRP), to assist in identifying land use change impacting CSTG and the importance of CRP lands in supporting habitat for CSTG nesting and brood rearing. Additionally, this project is partially supported through the United States Geological Survey (USGS) AmericaView program to promote research and education in remote sensing.

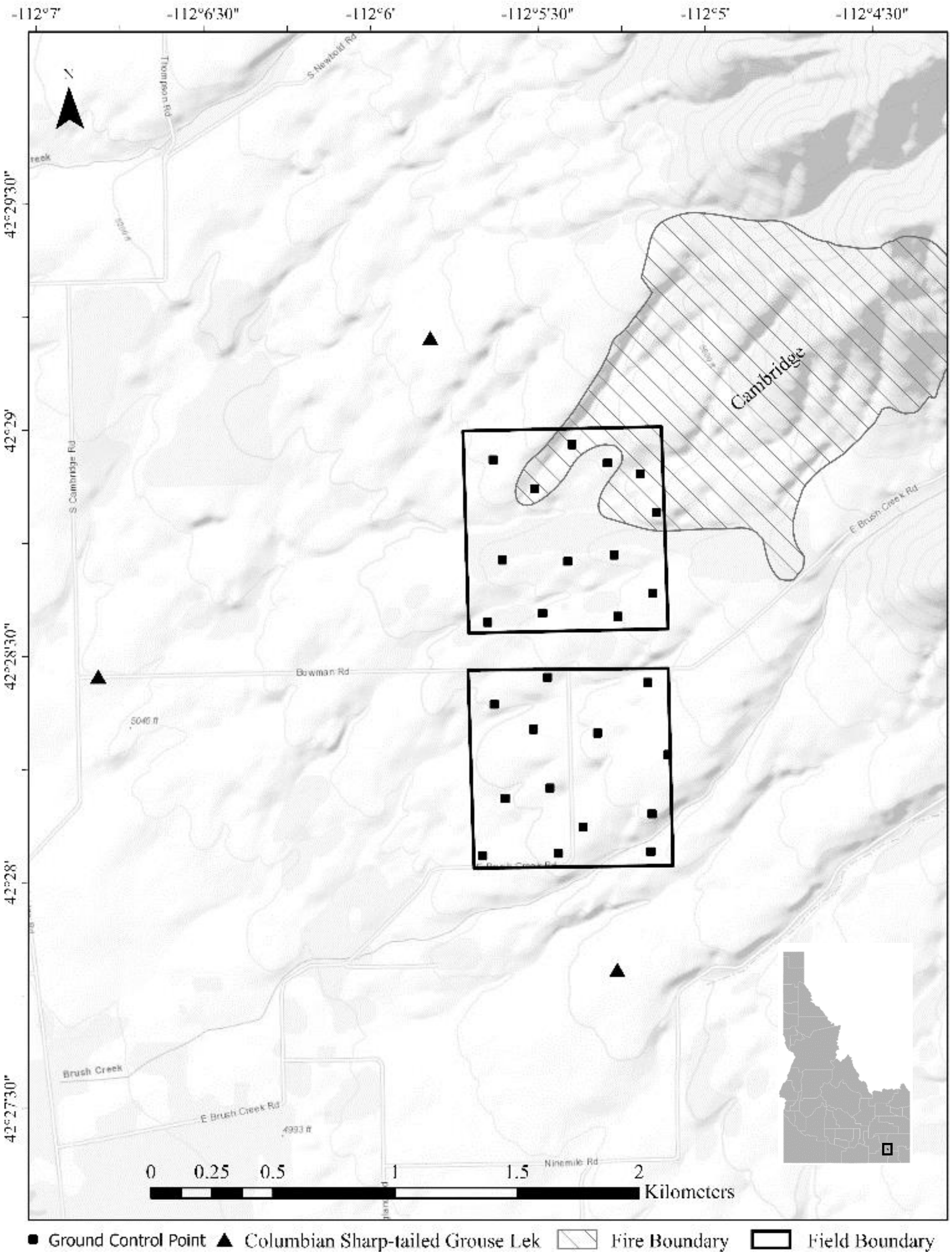

Figure 3. Conservation Reserve Program fields near Columbian Sharp-tailed grouse leks and the Cambridge wildfire (2014).

Chapter 2. Literature Review

2.1 Columbian Sharp-tailed Grouse Behavior and Habitat

Columbian sharp-tailed grouse (CSTG) generally subsist on several species of seasonal vegetation and insects, including plants native and non-native to the sagebrush steppe environment. Mixes of shrubs and forbs offer important habitat for CSTG, with species such as snowberry (*Symphoricarpos albus*), serviceberry (*Amelanchier alnifolia*), and chokecherry (*Prunus virginiana*) offering forage (Klott and Lindzey, 1990) and forbs to mid-height shrubs such as forbs and mid-heigh shrubs such as rabbitbrush (*Ericameria nauseosa*), antelope bitterbrush (*Purshia tridentata*), sainfoin (*Onobrychis arenaria*), yellow sweet clover (*Melilotus officinalis*), and also provide useful cover from predators (Davies et al., 2011). In addition to vegetation, insects such as Coleoptera, Hymenoptera, and Orthoptera (Giesen and Connelly, 1993) found in these mixed vegetation communities supplement CSTG diet. Studies of habitat impact from the increased presence of cattle are mixed. Marks and Marks (1987) predict increased presence of cattle may cause deteriotion of habitat and a corresponding hit to CSTG populations. Recent studies show livestock grazing may improve succession rates of big sagebrush in areas which have been replanted post fire (Copeland et al., 2021, Davies et al., 2020). Other studies show that long term grazing may negatively affect perrinnial native species, especially warm season grasses (Porensky et al., 2020). Jones (1966) highlights several segments of CSTG diet, specifically noting two instances of non-native vegetation (Dandelion, *taraxacum officinale*; and Cheatgrass, *Bromus tectorum*) entering the diets of CSTG. Jones measured the diets of CSTG comparatively by contrasting vegetation availability with the amount of vegetation digested and released in their droppings. The study showed avoidance of cheatgrass compared to its availability, and overabundance of common dandelion found in the diet compared to its relative availability, demonstrating plant availability does not necessarily affect preference in diet.

A lek is a relatively flat space, lightly vegetated and generally cleared of major obstructions where males of a given species compete for mating rights with females (Marks and Marks, 1987). CSTG are considered a “classically lekking species”, in that they generally follow the behavioral patterns associated with lekking species. A CSTG generally picks lek locations that fall upon ridges or other relatively flat and high places. They prefer locations with a mix of shrubs and native grass, but no high cover. While vegetation is present, it is often less prevelent than general CSTG habitat, and it is unclear what the underlying motivation is to select somewhat more dense cover compared with other lekking species (Klott and Lindzey, 1990). The males go to the lek to compete for a mate, the females perch along the outside of the lek to watch the ritualistic “dance” of the males, and decide which males to mate with (Marks and Marks, 1987). The population of a given lek remains relatively stable from year to year, because CSTG often return to the same leks over their lifetime (Marks and Marks, 1987). Lekking behavior and it’s connection to the proximal environment can be a useful tool to make inferences about behavior regarding preferred habitat, and allow us to track how LULC change impacts the population of CSTG. Counts at a given lek provide a metric for estimating the population of a specific area, because CSTG are unlikely to venture far outside the area surrounding the lek during the crucial mating and rearing period from March to June (Marks and Marks, 1987). A female CSTG will generally nest within ranges as close as 1.6 kilometers (Giesen and Connelly, 1993), as far as 4 km of the lek (Marks and Marks, 1987), and with 90% of nests falling within a 2.7 km radius (Proett et al., 2019). Quantifying and analyzing the relationship between CSTG lek population and historical LULC data will improve the ability to make predictions for how this species will response and adapt to changes in the enviornment. Additionally, the spatio-temporal relationships of wildfire and lek counts may provide clues about how CSTG will respond if a wildfire destroys their historical lek and surrounding nesting and brooding habitat.

The Conservation Reserve Program (CRP) began in 1985 with the passing of the 1985 Farm Bill (Food Security Act of 1985, 1985), and was continued by the Agricultural Improvement Act of 2018 (the 2018 Farm Bill) (Robbins, 2014). CRP has specific goals to reduce soil erosion, but has grown to include metrics for what to grow with a secondary goal of short to medium term restoration of plants that support the local ecology. This is accomplished using beneficial native and nonnative vegetation that maintain soil cover and lower erosion rates (Rodgers and Hoffman, 2005). CRP offers vital habitat for sage grouse (Schroeder and Haegen, 2012) as well as CSTG (Schroeder et al., 2000). CRP seems especially important for the CSTG, described as “benefitting CSTG more than any other prairie grouse” (Rodgers and Hoffman, 2005). CRP fields are managed to produce diverse, high quality plant habitat for pollinators (Calton, 2019). This has the added benefit of offering biodiverse landscapes that reduce landscape fragmentation, and provide ideal habitat for wildlife such as CSTG (Dunn et al., 1999).

Wildfires play a vital role in ecosystem health in sagebrush-dominated environments, but their heightened frequency over the period from 1950 to present (Weber, 2020) has facilitated the propagation of non-native annual grass species such as cheatgrass (Bradley et al., 2018). As fires burn larger or more resilient native vegetation cheatgrass will quickly re-establish making it difficult for native vegetation that have longer establishment periods (Billings, 1994a). Fragmentation and degradation of the sagebrush steppe environment is becoming more driven by wildfires as the severity and frequency of fires increase (Miller et al., 2009). Shifts in the ecology from shrub-dominated to annual grass-dominated landscapes excacerbate habitat loss for endemic species such as CSTG. These shifts lead to increased risk of fire and threaten adjacent agriculture and urban communities. As a response to this negative-feedback driven landscape evolution, sagebrush habitat conservation has become a focus of land management agencies.

2.2 Previous Studies of Land Cover Mapping and CSTG Population Trends

Initial studies from the 1950's indicate a relationship between the introduction of cultivation with the decrease in the population of CSTG over time in the state of Washington (Buss and Dziedzic, 1955). Classifying LULC for multiple timesteps can allow us to quantitatively study the impacts of LULC change on a population of birds (Jetz et al., 2007). Previous work by Calton (2019) quantified the impacts of landuse change southeastern Idaho on CSTG population change between 2001 to 2016 by using the National Land Cover Dataset (NLCD) (Jin et al., 2019). Calton (2019) cites misclassification of cover type in the NLCD as a potential source of error in measuring the impact of LULC on lek population changes. The NLCD is maintained and made available by the Multi-Resolution Land Characteristics (MRLC) consortium, a group of federal agencies with interest in mapping land characteristics. Until recently a major limitation of the 30-m resolution NLCD was its time availability, only snapshots in 2001, 2006, and 2016. The RSC product (Rigge et al., 2020) is a relatively new dataset available from MRLC that includes yearly (1984-2019) layers of fractional cover as a percent of the pixel area and includes cover types of: shrub, herbaceous, bare ground, litter, sagebrush, big sagebrush and annual herbaceous. The fractional component layers have the potential to be useful for identifying ideal CSTG habitat. Unfortunately, the NLCD represents limited time span of 20 years compared to over a century of CSTG population decline.

2.3 Remote Sensing Platforms

2.3.1 Satellite Sensors

The longest continuously operating series of satellites is Landsat. Landsat offers the greatest temporal coverage of data providing a 15 day interval of multispectral data (Table 1. Remote sensing platforms). Landsat data collection began with the launch of Landsat 1 in 1972, marking the beginning of long term satellite data collection. Landsat 4 (LS4) and 5 (LS5) have the same thematic mapper (TM) sensor, that has been subsequently re-calibrated to produce similar imagery to the modern era Landsat satellites (Markham and Helder, 2012). LS4 and LS5 also output comparable bands to the Landsat 8 (LS8) Operational Land Imager (OLI) sensor, with the addition of the cirrus and an ultra-blue bands to LS8. Landsat 6 failed to achieve orbit, and while Landsat 7 has produced useful data that is consistent with previous missions using the Enhanced Thematic Mapper (ETM), it suffers scan line error (SLE) which creates extra work to correct. Drawing conclusions from imagery that includes SLE error should be avoided. The LS5 and LS8 satellites offer nearly continuous data collection from 1984 to present, with LS5 operating from 1984 through May 2012, and LS8 operating from April 2013 to present. Comparison of vegetation indices created from LS5 and LS8 show a relative bias of 1.5-5% for the visible bands, and is attributed to updated atmospheric correction algorithms between the two sensors (Zhu et al., 2016). In 2017 the USGS released Landsat Analysis Ready Data (ARD), which are atmospherically corrected, projected, gridded, and calibrated relative to each other and produce consistent and comparable data (Qiu et al., 2019). Unfortunately, recent studies have shown inconsistent error with several Landsat 5 products due to orbital changes of the Landsat 5 platform, specifically during period from 1995-2000 compared with 2007-2011 (Zhang and Roy, 2016).

Table 1. Remote sensing platforms

Sensor / Platform	Collection period	Resolution	Bands
Landsat 5	03/1984 – 06/2013	30-meter, 120-m thermal, 15 Day	RGB, Near infrared, Shortwave infrared, Thermal Infrared
Landsat 7	04/2015 – present	30-meter, 60 (30) meter, 15 Day	RGB, Near infrared, Shortwave infrared, Thermal Infrared
Landsat 8	02/2013 – present	30-meter, 100-meter thermal, 15 Day	Coastal Aerosol, RGB, Near infrared, Cirrus, Shortwave infrared, Thermal Infrared
Sentinel-2	06/2015 – present	10-meter, 15 meter Red Edge, 60-meter Shortwave Infrared, 5 Day	RGB, Near infrared, Shortwave infrared, Thermal Infrared, Red Edge
Aqua/Terra MODIS	12/1999 – present	250-meter, 1-2day	RGB, Near Infrared
National Agricultural Imagery Program	2003 - present	1 meter, yearly	RGB, Near Infrared
Micasense + Sony α6000, UAS Borne	June 2020	7-cm Multispectral, 2.5-cm True Color	True Color, RGB, Near infrared, Shortwave infrared, Thermal Infrared, Red Edge, digital surface model

2.3.2 UAS Sensors

UAS borne multispectral imagery is becoming common in scientific remote sensing applications (Watts et al., 2012). UAS data can be collected on demand and customizeable sensor payloads tailored for specific needs. UAS can be split into three major categories based on flight styles, fixed wing, multirotor, and hybrid models (Dündar et al., 2020). Fixed wing UAS can carry heavy payloads over long distances, but generally must fly at higher altitudes and at faster speeds. Fixed wing UAS are used for collecting imagery over large areas, at cost to spatial resolution. Additionally, they require a runway, or launch mechanism to take off and land. Multirotor UAS are able to carry payloads similar to fixed wings, but have limited flight time due to energy consumption and battery weight. Multirotor UAS take off vertically, fly at low altitudes and are useful for collecting data over smaller areas with fine spatial resolution. Hybrid model UAS fit in a space between multirotor and fixed wing, with motors that facilitate vertical takeoff and landing (VTOL) without the need for a luanching mechanism or runway.

A variety of sensors can be mounted to UAS depending on the type of data or analysis one wishes to perform. In this study, we used the Micasense RedEdge Dual Camera System (MRDCS), a multispectral camera containing 10 bands which are spectrally similar to bands found on the Sentinel-2 satellite. These bands are useful for remote sensing of vegetation, and the MRDCS was used for observing spectral variation in potato plants to detect Potato Late Crop Blight (Fernández et al., 2020), as well as aerial crop monitoring and yield estimation for perrenial ryegrass (Pranga et al., 2021). Similar to Sentinel-2 the MRDCS observes along the red edge, an area of the electromagnetic spectrum that is useful for determining characteristics of plant health (Ghosh et al., 2018).

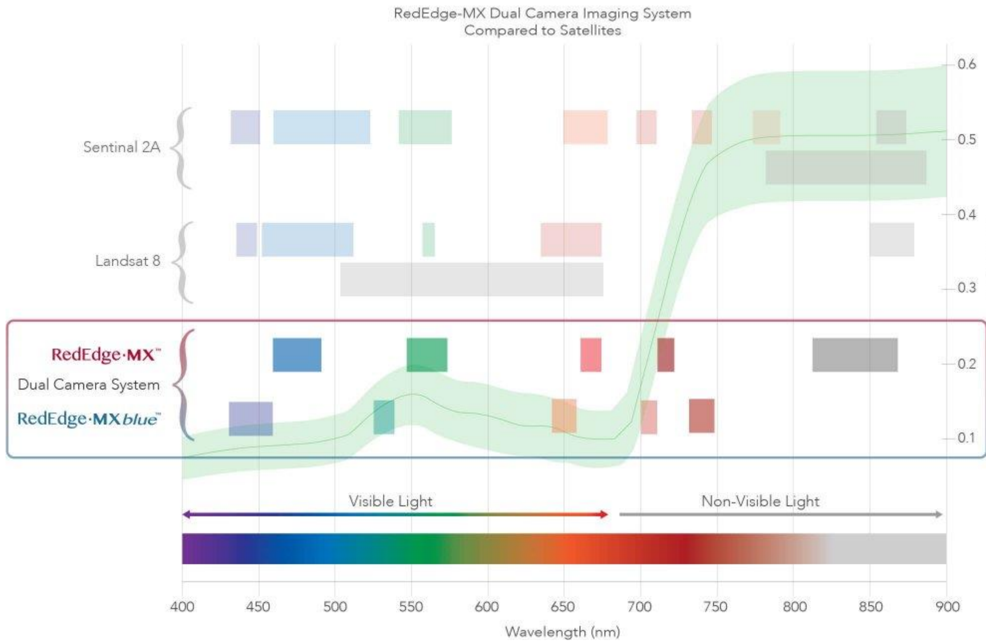

Figure 4. Spectral Bands for Landsat 8, Sentinel 2A and the Micasense Dual camera system (Source: https://micasense.com/dual-camera-system/)

This project also makes use of the Sony α6000 mirrorless digital camera for true color imagery collection. Imagery collected using UAS is commonly combined into orthomosaic imagery, with ground resolution calculation shown in Figure 5. Ground Sample Distance calculated from the calculated sensor dimensions, focal length, and height of flight. The combination of images using photogrammatric software also facilitate the creation of structure from motion model of surficial features (Westoby et al., 2012). Digital surface models derived from SFM models have been used for extensive scientific modeling including vegetation height and estimation of above ground biomass (DiGiacomo et al., 2020), produce forest canopy models to inform river temperature (Dugdale et al., 2019), and high precision erosion monitoring (Gillan et al., 2017).

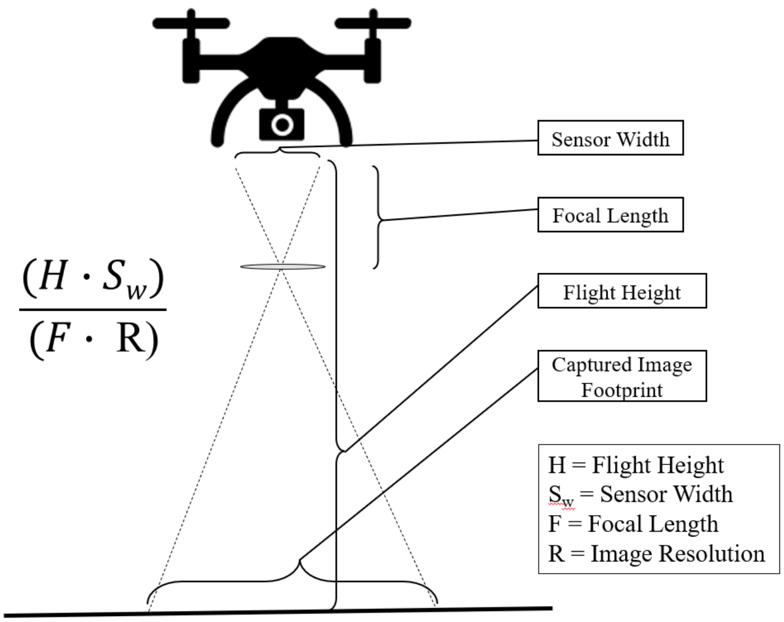

Figure 5. Ground Sample Distance calculated from the calculated sensor dimensions, focal length, and height of flight.

2.4 Image Classification of Vegetation Composition and Habitat

Random Forest (RF) is a supervised machine learning algorithm that uses training data to make either regression predictions for numerical values, or class predictions for discrete classes. The RF algorithm creates a group of heuristic decision trees, each of which makes predictions based on binary output; the final class or numerical value is chosen from the highest accuracy tree (Gislason et al., 2006). Each tree in a RF model is sub-sampled which splits the training samples beyond training and testing. This allows RF to take advantage of large training datasets while reducing the amount of overfitting the model to the training data by splitting up correlated variables in the samples. Support Vector Machine (SVM) is another supervised machine learning algorithm that works by assigning values in training data to a vector space, and the model maximizes or minimizes the distance between categories within the space. A prediction is made based on where any new data fits within that vector space.

An accurate classification is desirable to make any inference on the influence of LULC change to changing CSTG population in southeast Idaho. Several techniques of classification using modern machine learning algorithms integrating multispectral and hyperspectral data inputs generate accurate LULC (Petropoulos et al., 2012). The literature has several comparisons of machine learning algorithms with new techniques for implementing artificial neural networking algorithms for LULC classification. These generally demonstrate the dominance of artificial neural networks for returning accurate classification maps (Rogan, 2008). A study comparing SVM, RF, and k-Nearest Neighbor (kNN) demonstrated accuracies of 90-95% when using training data from Sentinel-2 multispectral imagery to classify LULC in the Red River Delta of Vietnam (Thanh Noi and Kappas, 2017). Another survey study of multiple algorithms identified the SVM algorithm as a top performer, showing accuracy as high as 90% when looking at an urban area in the Haidian District of Beijing (Qian et al., 2015). The highest accuracies (>93.5%) in image classification require a target number of at least 750, or 0.25% of the total pixel area, per class (Thanh Noi and Kappas, 2017). Consistently SVM and RF are considered top contendors for high levels of accuracy in the field of image classification, but more work could be done examining environments like the sagebrush steppe.

Chapter 3. Predicting Columbian Sharp-tailed Grouse Mean Decadal Lekking Population by Analyzing the Relationship Between Land Use and Land Cover Trends in Southeastern Idaho

3.1 Introduction

Columbian sharp-tailed grouse (CSTG), *Tympanuchus phasianellus columbianus* are a species of small upland game bird endemic to western North America. The historic range of CSTG , once extended from British Columbia to northern New Mexico, covering most of Idaho and Utah, as far west as Washington, Oregon, and the northeast corner of California, and as far east as western Montana, Wyoming, and Colorado; in recent decades CSTG territory shrank to nearly 5% of the former range (Andersen et al., 2015). This chapter examines several habitat disturbances including fire activity, Conservation Reserve Program (CRP) area, and land cover composition within a 4 km radius of 318 lek sites in southeastern Idaho over the time period between 1985 and 2019.

CSTG have only three remaining populations: in British Columbia, northern Colorado, and southeastern Idaho, with the southeast Idaho contingent representing 60% of CSTG in the United States (Hoffman and Thomas, 2007). While this represents a robust percentage of the population, it has been considered to be under pressure from habitat degradation and loss due to the expansion of agriculture in the first half of the 20 century (Buss and Dziedzic, 1955; Hoffman and Thomas, 2007). The decline in population is also attributed to over-harvest from hunting (Giesen and Connelly, 1993). CSTG is currently listed as a “Species of Greatest Conservation Need” in the Idaho State Wildlife Action Plan, and US Fish and Wildlife Service has been unsuccessfully petitioned twice to add the CSTG to the endangered species list (Andersen et al., 2015). Southeast Idaho encompasses the northeast reach of the Great Basin of

North America and is historically covered with a mix of sagebrush-steppe rangeland, riparian vegetation along the Snake River and its tributaries with mixed highland forest. Understanding the factors that impact the population of CSTG in southeast Idaho is important because it is home to a substantial percentage of the few remaining healthy populations (Figure 1. Historic and Current Range of Columbian Sharp-tailed Grouse from Andersen et al., 2015.).

CSTG have white and brown feathers with black spots; males are distinguished by a conspicuous yellow eye crest and red marking along the throat. CSTG generally subsist on several species of seasonal vegetation and insects (Jones, 1966), including plants native and non-native to the brushland environment. Mixes of shrubs and forbs offer important habitat for CSTG, with species such as snowberry (*Symphoricarpos albus*), serviceberry (*Amelanchier alnifolia*), and chokecherry (*Prunus virginiana*) providing important forage (Klott and Lindzey, 1990); while forbs and mid-heigh shrubs such as rabbitbrush (*Ericameria nauseosa* or formerly *Chrysomthamnus spp*), antelope bitterbrush (*Purshia tridentata*), sainfoin (*Onobrychis arenaria*), yellow sweet clover (*Melilotus officinalis*), which are also useful as cover from predators (Davies et al., 2011). In addition to vegetation, insects found in these mixed vegetation communities from the Coleoptera, Hymenoptera, and Orthoptera Order (Giesen and Connelly, 1993) supplement the CSTG diet.

CSTG habitat is impacted by the increased presence of cattle which may cause deteriotion of habitat and supported wildlife communities (Marks and Marks, 1987). Localized grazing can improve succession rates of big sagebrush in areas that have been replanted post fire (Davies et al., 2020, Copeland et al., 2021), while long-term grazing negatively affects perrinnial native species, especially warm season grasses (Porensky et al., 2020). CSTG-related similar Sharp-tailed Prairie grouses (*Tympanuchus* spp.) show preference for areas managed using rest-rotation grazing, which is the practice of grazing an area with a rotation of seasons off to allow for vegetation to recover (Milligan et al., 2020).

CSTG congregate on ritual mating grounds called leks, to compete for mating rights. CSTG leks are generally located on high points such as ridges or hills and are vegetated with a mix of shrubs, native grass, but no high cover. Lekking behavior and its connection to the proximal environment can be a useful tool to make inferences about behavior regarding preferred habitat and allow researchers to track how land use and land cover (LULC) change impacts the population of CSTG. Nesting and brood rearing often occurs within proximity to the lek location, with ranges from 1.6 kilometers (Giesen and Connelly, 1993), and as far as 4 km (Marks and Marks, 1987) from the lek. Its estimated that 85% of studied females nest within 2 km of a lek (Boisvert et al., 2005), and 90% of nests fell within a 2.7 km radius (Proett et al., 2019). The population of a given lek remains relatively stable from year to year, because CSTG often return to the same leks over their lifetime (Marks and Marks, 1987).

Wildfires play a vital role in ecosystem health even in sagebrush-dominated environments but threatens to fundamentally change the sagebrush-steppe. Wildfire are most commonly ignited via lightning, although they may occur from other unnatural processes, such as from discarded cigarettes (Prestemon et al., 2013). There is a rising frequency of fires in the western United States (Weber, 2020), and as global temperatures increase it is predicted there will be an increase in area burned for the western United States (Kitzberger et al., 2017). Anthropogenic climate change also has indirect impact on wildfires, such as increased average wind speed which increases the rate of fire spread (Fried et al., 2004). These fires often negatively affect ground bird populations because they destroy good ground habitat (Noson et al., 2006). The increasing presence of fire has facilitated the propagation of non-native annual grass species such as *Bromus tectorum* (cheatgrass) (Bradley et al., 2018). Especially of concern is as fire burn larger or more resilient native vegetation, cheatgrass will quickly re-establish, making it difficult for native vegetation that requires longer succession periods (Billings, 1994b). Fragmentation and degradation of the sagebrush steppe environment is becoming more driven by wildfires as the severity and frequency of fires increase (Miller et al., 2009). Landscape level shifts in the ecology from shrub-dominated to annual grass-dominated leads to increased risk of fire. Sagebrush-steppe habitat conservation has become a focus of land management agencies as a response to this negative-feedback driven landscape evolution.

Recent development and release of the RSC has enabled the analysis of data over a massive scale allowing us to make statistical inferences about trends in LULC change. The RSC contains yearly percent cover for each year between 1984 and 2018, as well as an overall trends dataset. We gathered statistics about the habitat within the nesting and brood rearing habitat for the CSTG using the RSC time series trends dataset that is available from the Multi Resolution Land Characteristics Consortium (MRLCC) (Rigge et al., 2020).

Programs like the CRP offer vital habitat for many species of sage grouse (Schroeder and Haegen, 2012) and are especially important for CSTG (Schroeder et al., 2000). The CRP program benefits CSTG more than any other prairie grouse (Rodgers and Hoffman, 2005), offering hundreds of acres of nesting and brood-rearing habitat. The CRP began in 1985 with the passing of the 1985 Farm Bill (Food Security Act of 1985, 1985), with specific goals set out to reimburse farmers for short to medium term restoration of plants which support the local ecology, using beneficial native and nonnative vegetation to maintain soil cover and lower erosion rates (Rodgers and Hoffman, 2005).

Determining true population from lek counts of a given species of bird is somewhat complicated because of the imperfect nature of observation error. A study from Copeland (et al., 2013) examined sage grouse population trends in Wyoming with relation to energy infrastructure expansion over time. Copeland used a linear regression of the log of the mean population abundance to create a sage-grouse population decline function to get around the large number of zero count leks, with an r^2 of 0.82 and 95% confidence. Another study of greater sage grouse lek counts found discrepancies between counts and actual population due to movement dynamics of males in each season (Blomberg et al., 2013). Other research indicated use of probability density functions to grid populations using population point data (Coates et al., 2013). This is done using the Kernel Density function in ArcGIS, that uses the Quartic kernel formula (Silverman, 1998) to generate a density in each pixel within a certain radius and generate a raster.

The aim of this research is to understand the how the trends CSTG lekking population's correlate with changes in LULC in southeast Idaho. Over this chapter we examined the and RSC LULC trends, CRP and wildfire location data to determine if there is spatio-temporal correlation with lek counts.

3.2 Methodology

3.2.1 Study Area

The study area covers Bannock, Power, and Oneida counties in southeastern Idaho (Figure 6). This area falls in the northeast ranges of the Great Basin physio geographic region, along the border of the Snake River Plain. The sagebrush-steppe of this area in southeastern Idaho includes many species of typical vegetation. Three species of sagebrush: Big sagebrush (*Artemisia tridentata spp., wyomingensis*), Dwarf sagebrush (*Artemisia arbuscula ssp. thermopola*), Threetip sagebrush (*Artemisia tripartita*). Four species of perennial grasses cover the same area: Fescue-wheatgrass (*Festuca-Agropyron*), Wheatgrass-bluegrass (*Agropyron-Poa*), Mountain Brome (*Bromus marginatus*), Snake River Wheatgrass (*Elymus wawawaiensis*). Finally, four species of juniper represent the sagebrush-steppe: Ground Juniper (*Juniperus communis*), Rocky Mountain Juniper (*Juniperus scopulorum*), Utah Juniper (Juniperus osteosperma), Western Juniper (*Juniperus occidentalis*). This area also includes many invasive and noxious species of weeds, important for this study is cheatgrass (*Bromus Tectorum*). The study area also contains a useful proportion of area containing a healthy population of CSTG, covering 314 sampled lek sites. These three counties have been affected by 968 fires over the period of 1939-2018, and 797 of which occurred 1984-2018. Fires in general are considered to be a major driver of vegetation change, facilitating conversion from native to nonnative vegetation (Bradley et al., 2018).

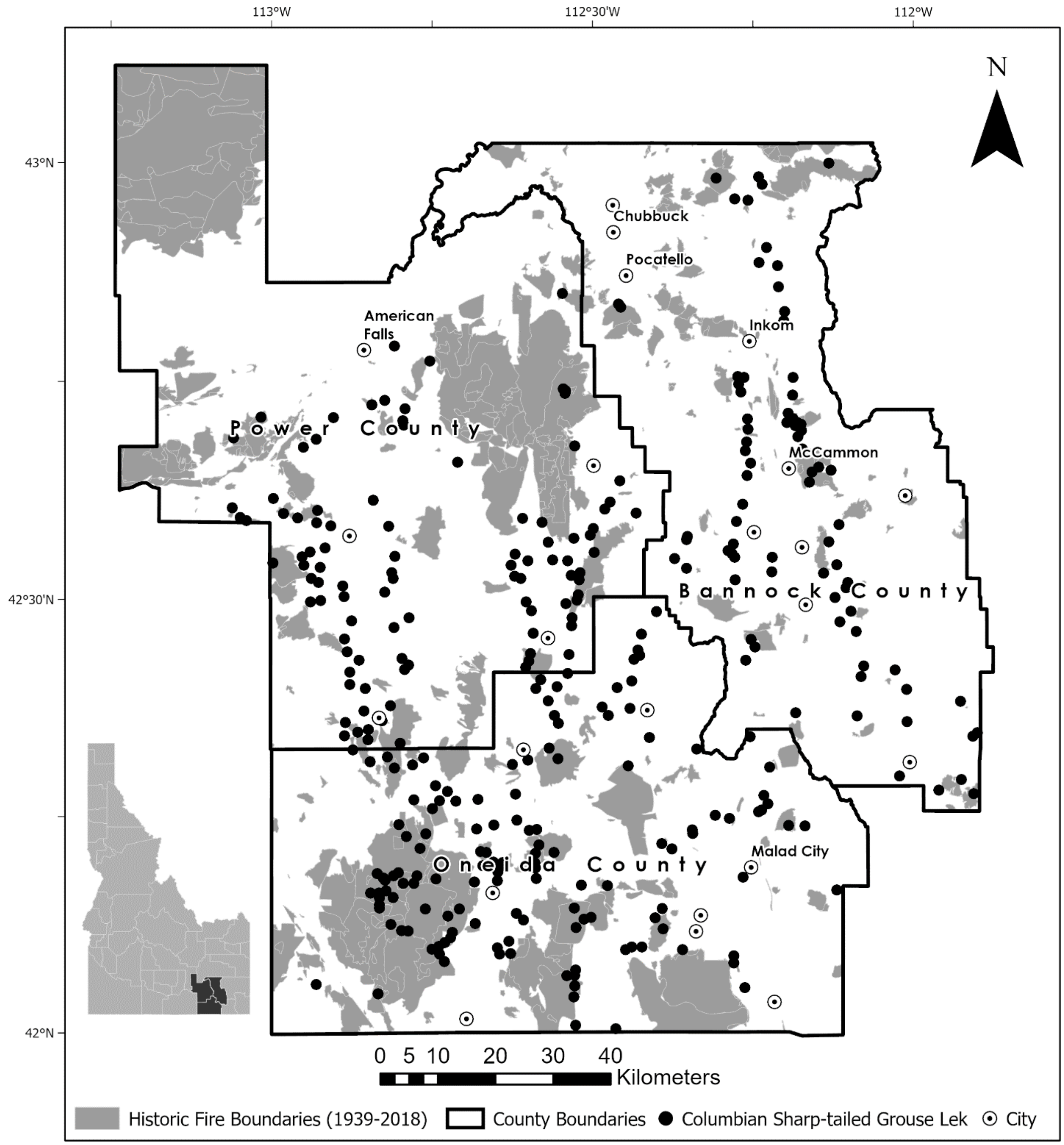

Figure 6. Fire Boundaries and Columbian Sharp-tailed lek locations in Bannock, Power and Oneida counties.

3.2.2 Data Sources

3.2.2.1 Rangeland Shrub Component Time Series Trends Raster Dataset

The Multi Resolution Land Characteristics Consortium (MRLCC) has released data that visualizes models for estimating LULC trends. The RSC dataset was made using a machine learning algorithms to model pixel fractional coverage, and validated using *in situ* and remote sensed data (Rigge et al., 2019, Shi et al., 2020). This dataset includes fractional cover as a percent of the pixel area (e.g., 45 for 45% sub-pixel cover) for each year between 1984 – 2018. The six LULC classes used are: shrub, herbaceous, bare ground, litter, sagebrush, big sagebrush and annual herbaceous. Masked area generally encompasses urban / infrastructure, agriculture, water, and high elevation. It also includes a time series trends layer that assigns a value on a per pixel basis for the slope, standard deviation, and t-score of the data, for each landcover type, over the entire time period.

3.2.2.2 Historic Fire Polygon Database

Fire boundary data was obtained from Idaho State University Geographic Information Systems Training and Research Center Historic Fires Database. This database was created by aggregating wildfire perimeters from interested authoritative sources including: the US Forest Service, Bureau of Land Management, US Geologic Survey, National Interagency Fire Center, Idaho Department of Lands, and the California Department of Forestry and Fire Protection. This fire database contains wildfire perimeters and other data for 967 fires in Bannock, Power, and Oneida counties between 1939-2019.

3.2.2.3 Idaho Fish and Game Lek Count Dataset

Idaho Fish and Game provided spreadsheet of 314 CSTG lek locations and counts and their locations within Bannock, Power, and Oneida counties. The count dataset contains 2078 counts for each lek over the period from 1985 to 2018. CSTG leks are surveyed in the spring when CSTG gather for male birds to display ritual dancing display. Counts are performed 30 minutes before sunrise to 1.5 hours after sunrise, over three consecutive days. Standardized survey protocol provides population estimate within 90% confidence interval (Andersen et al., 2015). Lek population data was transformed into a value used to examine the trend over time by calculating the mean count for each decade per lek, and then subtracting those mean values. Leks that only had a single count during time period were removed. This decadal mean count value was used to determine whether a lek had increasing / decreasing trend over several decades. The change in mean lek population data displays normal distribution across the dataset Figure 7.

Change in Mean Lekking Population

1984-2018

Bannock, Power, and Oneida Counties, Idaho

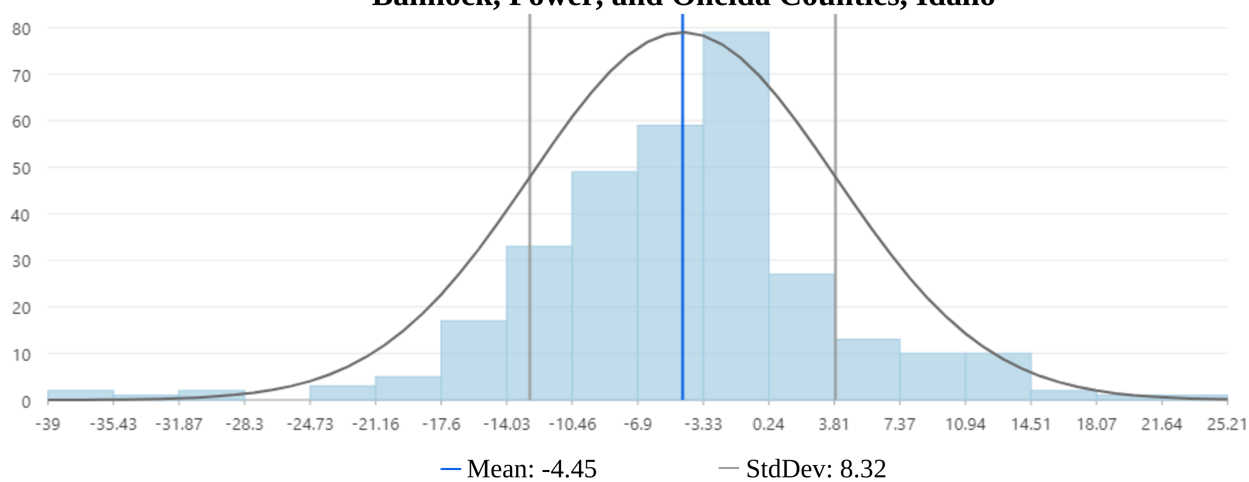

Figure 7. Distribution of Columbian Sharp-tailed Grouse lekking population change between 1984 and 2018 for Bannock, Power, and Oneida Counties, Idaho.

Distribution of Columbian Sharp-tailed Grouse lekking population change between 1984 and 2018 for Bannock, Power, and Oneida Counties, Idaho..

3.2.2.4 Conservation Reserve Program Parcel Polygon Data

This polygon dataset contains parcel information from the United States Department of Agriculture Farm Service Agency for CRP area within Bannock, Oneida, and Power Counties, over the time period from 2012-2018. The modern CRP was established with the 1985 Farm Bill (Food Security Act of 1985, 1985), farmers enrolled are paid to plant species that are beneficial to the environment and enhance the local habitat. These polygon data contain metadata about the owner, county, dates when the CRP agreement expires. This data was shared under a memorandum of understanding, and in order to protect confidentiality of landowner's locations have been ambiguated for output products.

3.2.3 Data Processing

3.2.3.1 Buffering and Zonal Statistics

This project used ArcGIS Pro 2.7 to process images, points, polygons, and generate statistics. Lek location points were buffered to 4 km to create zones representing the nesting and brood rearing habitat of the CSTG. The RSC time series trend slope raster dataset was sampled within a 4 km radius for each site and added to an attribute table for each lek. The 4 km buffer around each lek contains an amount of masked area which was used to generate a mean trend value for all lek area in the actual measured sagebrush steppe. Wildfire boundaries for 797 wildfires were intersected to determine the area burned between 1984-2018 that was within the 4 km nesting and brood rearing area for each lek. The same method was used to determine the percentage of CRP area fell within the 4 km buffer. Both of those parameters were added to the lek count attribute table, which also contains slope trends for each cover class and the area burned (1984-2018), and mean percent CRP (2010s). We decided to use a decadal mean change in population to measure the lekking population change over time. This was used to overcome yearly fluctuations in lek count which may arise due to animal behavior. A simple subtraction of before and after was used to examine the trend change over time. The mean decadal population trend value was input into the kernel density tool in ArcGIS, using a search radius of 10 km, to create a surface raster that illustrates the mean population change. 10 km was chosen to create a raster including the entire area.

3.2.3.2 Spatial Autocorrelation and Geographic Weighted Regression

The Spatial Autocorrelation (Global Moran's I) tool examines the spatial relationships and the parameter values to determine the level of clustering or randomness within a given dataset. I used a fixed Euclidean distance of 10 km to build neighborhoods to capture the relationship between leks within the same valley, but to avoid connecting to populations across mountain ranges. Spatial autocorrelation was determined for the change in decadal mean lek count, mean trend for all classes, and mean wildfire and CRP area parameters.

Geographically weighted regression (GWR) is a tool in ArcGIS that creates a local model across a nearby neighborhood of points to perform a normal regression using dependent and independent variables. This is accomplished using a kernel algorithm that reduces the influence of geographically distant points on the regression calculation. GWR uses several methods for designing model neighborhoods, such as closest neighbors, golden search or manual interval. We used a manual Euclidean distance of 4 km for the neighborhood. The GWR model we created used the kernel density of the change in decadal mean population as the dependent variable, with CRP area, fire area, shrub, and sage slope trend as predictive variables. We used the continuous (gaussian) prediction as an additional parameter for model generation. GWR returns a coefficient of determination correlation value between the tested variables, charts showing several histograms of the standard residual, and a prediction raster for the dependent variable.

3.3 Results

3.3.1 Land Use and Land Cover Trends

We examined the RSC landcover and trends datasets, using the mean trend value for each class within 4 km of each lek within the study area. The RSC slope trend value is given as a unitless, slope value for the trend line of percent cover by pixel. Our study area has low positive trends for Sage, Shrub, Herb, Annual Herbaceous, and Litter classes; and a low negative trend for Bare ground class (Table 2. CRP, Fire and Land Use and Land Cover Trend. The standard deviation for each class is given and represents the variation in percent cover by pixel for each year. Our results show that Bare and Shrub classes had the widest variation of percent cover. Bare has a standard deviation of 5.29% cover, and Shrub 4.95%. Litter has the lowest overall variation at the lek scale, with a standard deviation of 1.65%. During the period of 1985-2018 there were 797 fires impacting 22.23% of nesting and brood rearing area with a standard variance of 26.86%. Historically available data shows in the same areas over the period from 1939-1985, there were 170 fires covering 4.21% of the nesting and brood rearing area. This represents an increase in fire disturbed area by 466.17% within CSTG nesting and brood rearing area.

Table 2. CRP, Fire and Land Use and Land Cover Trends for Columbian Sharp-tailed Grouse nesting and brood rearing habitat. Each class shows the mean of each leks LULC trend slope, max and min values for 1985 and 2018. CRP and burned area do not have trend slopes, and CRP data is not available for 1985.

Land Cover n=314	**Sage**	**Shrub**	**Herb**	**Annual Herb**	**Litter**	**Bare**	**CRP Area**	**Burned Area**
Mean (Trend Slope)	0.016	0.0189	0.0178	0.0048	0.0194	-0.0650	NA	NA
StdDev	3.068	4.95%	3.96%	2.199%	1.653%	5.289%	12.7%	26.86%
Mean (% Cover) 1985	11.69%	20.84%	29.91%	7.13%	18.57%	36.12%	NA	4.219%

Mean (% Cover) 2018	14.25%	23.54%	30.68%	7.67%	20.60%	30.71%	16.51%	22.23%
Min 1985	2.926%	8.636%	21.05%	2.039%	12.32%	13.75%	NA	0
Max 1985	21.77%	41.01%	38.94%	11.14%	23.81%	57.76%	NA	65.3%
Min 2018	2.329%	3.49%	22.71%	1.209%	16.14%	11.35%	0	0
Max 2018	23.86%	42.95%	40.01%	13.53%	23.88%	50.79%	52.66%	99.68%

3.3.3 Spatial Autocorrelation Results

Spatial autocorrelation for each variable is shown in Table 3 Spatial Autocorrelation for all Land Cover and Land Use Classes, as well as Fire and Conservation Reserve Program Area, for Bannock, Power, and Oneida Counties. There is significant clustering for all independent variables examined, which was expected given sample values were generated via zonal statistics for overlapping zones. The change in decadal mean lek count has a z score of 1.597 and a Moran's I value of 0.0425, and is not significantly different from random.

Table 3 Spatial Autocorrelation for all Land Cover and Land Use Classes, as well as Fire and Conservation Reserve Program Area, for Bannock, Power, and Oneida Counties.

Spatial Autocorrelation N = 314	Moran's I Value	Z-score	P value	Clustering
Change Decadal Mean Lek Count	0.042476	1.597083	0.110247	Random
Sage Trend	0.75549	26.40511	<0.0001	Clustered
Shrub Trend	0.732809	25.645803	<0.0001	Clustered
Annual Herbaceous Trend	0.654932	22.93432	<0.0001	Clustered
Herbaceous Trend	0.74472	26.043629	<0.0001	Clustered
Bare Trend	0.787428	27.588852	<0.0001	Clustered
Litter Trend	0.733697	25.691991	<0.0001	Clustered
Fire Area	0.379144	13.309288	<0.0001	Clustered
CRP Area	0.767351	26.807552	<0.0001	Clustered

3.3.4 Regression Results

Geographically weighted regression was used to describe the relationship between LULC and the kernel density of mean population decadal change. Sage Trend, Shrub Trend, CRP Area and Fire Area have the highest r^2 among single variable models identified using exploratory regression. R^2 values illustrate the strength of the relationship, and CRP area has the highest r^2 and adjusted r^2 among this group, with 0.957 and 0.938 respectively (Table 4). Two variable predictive models showed multicollinearity between sage and shrub cover preventing modeling with those two land cover classes. Calculation of relationship for all other two variable combinations was able to be performed. Of the two-variable regressions, the combined Sage and CRP model produced the best r^2 and adjusted r^2 for predicting the change in the mean decadal lek population, 0.965 and 0.943. Of the single variable and dual variable regression models, the single variable CRP area had the lowest corrected Akaike information criterion (AICc) score of -1844.3, lower than the two variable model using CRP and Sage which has a slightly higher adjusted r^2 value.

Table 4. Geographic weighted regression results which demonstrate the relationship between the kernel density of the change in mean lek count (Per decade) and a specific land cover characteristic. Of the land cover classes, sage and shrub had significant relationships with sage being the strongest relationship.

Model	R^2	AdjR^2	AICc	Effective Degrees of Freedom
Shrub Trend	0.948	0.923	-1778.7	212.81
Sage Trend	0.949	0.925	-1787.7	212.56
Fire Area	0.944	0.918	-1762.6	215.35
CRP Area	0.957	0.938	-1844.3	214.12
Fire+CRP	0.962	0.940	-1812.2	194.75
Fire+Sage	0.956	0.928	-1753.5	191.43
CRP+Sage	0.965	0.943	-1823.9	192.39

3.4 Discussion

All of the analyzed independent variables showed evidence of spatial autocorrelation, with high levels of confidence. If there is significant clustering within a variable, it may indicate bias in the model due to observations not being independent of each other. Likewise, significant dispersal of variable also indicates bias. Conceptually, the autocorrelation results for independent variables make sense because the data represents values sampled from overlapping 4 km buffer zones that describe the nesting and brood rearing habitat around a given lek. Additionally, there are ecological, spatial controls on vegetation land cover that are governed by physical geographic variables, such as certain vegetation preferring south facing slopes, or clustering within a valley and avoiding growing on steep slopes. The apparent, random level of clustering within the lekking population is expected. Birds from different leks may share the same habitat, but individuals are unlikely to attend more than one lek during a mating season, and there is evidence they return to the same lek year after year (Marks and Marks, 1987).

Wildfire area is an interesting parameter to examine as it describes the binary of disturbed and undisturbed land. This does not take into account that area within the perimeter is not equally burned or that some affected areas have been burned several times. This complication is compounded as wildfire often converts long living native vegetation into annual and invasive cheatgrass (*bromus Tectorum*) that reaches peak greenness in the early parts of summer, and browns down by July, right at the beginning of fire season (Clinton et al., 2010). The average percentage of burned area substantially increased from historic value, covering a mean of 23.9% of any given lek in 2018, but over 1985-2018, the mean annual herbaceous land cover trend had the lowest trend slope value of 0.0048. This is low growth trend but not low cover value, which means percentage of cover annual herbaceous land cover has stayed constant over the period, ranging between 2-11% in 1985, and 1-13.5% in 2018.

The change in the decadal mean lek population seems to have geographic correlation with wildfire area, but the results are the lowest of our models. This may be due to the binary nature of disturbed vs undisturbed land unable to be accurately quantified for our model. There are places in our study area which have been repeatedly impacted by fire, that also geographically correlate with population loss. Several areas impacted heavily by fire also show low population change values as well. Several studies in the supporting literature make the claim that the CSTG greatly benefits from CRP and our data appears to support that assertion. Several leks in our study area that have positive population change are in or near high concentrations of CRP land, which is also highlighted in our model that quantifies the relationship.

Geographic weighted regression results generally describe a solid relationship between LULC and CSTG mean decadal population change. Some groups of LULC variables capture the same relationships, such as sage and fire being intertwined; others are based on the same datasets with tweaks to some input variables, such as shrub and sage trends from the RSC dataset. For this reason, we are skeptical of all two variable models that may show collinearity. While the Sage and CRP combined model had the highest r^2, generally the principle of parsimony that the simplest model will generally be the best. In this case, the AICc value being lower demonstrates clearly that the single variable model (CRP) is better. The gain of 0.008 r^2 value in the 2-variable model (Sage and CRP) does not outweigh the uncertainty of using an additional variable. We find the best fit model for predicting mean decadal population change at a given lek is made by examining only the amount of CRP landcover overlapping with the nesting and brood rearing habitat within 4 km of a lek.

Chapter 4. Using Uncrewed Aircraft Systems Multispectral Imagery to Map Columbian Sharp-tailed Grouse Nesting and Brood Rearing Habitat in Wildfire affected Conservation Reserve Program Fields

4.1 Introduction

Landscape and habitat fragmentation, loss, and degradation have historically been problem in Idaho. In 1985 the passing of the 1985 Farm Bill (Food Security Act of 1985, 1985), created the United States Department of Agriculture Farm Service Agency's Conservation Reserve Program (CRP). The CRP program reimburses farmers for short to medium term restoration of plants which support the local ecology, using beneficial native and nonnative vegetation to maintain soil cover and lower erosion rates (Rodgers and Hoffman, 2005). CRP also offers vital habitat the Columbian Sharp-tailed Grouse (CSTG) (Schroeder et al., 2000), and is described as "benefitting CSTG more than any other prairie grouse" (Rodgers and Hoffman, 2005). CRP vegetation is important for providing cover from predators and a rich source of insects for chicks and young birds to eat. Understanding the composition of CRP in an area where the CSTG are actively raising young can inform researchers about the potential benefits of CRP to CSTG and other wildlife. The current practice for planting in CRP fields recomends a combination of forbs, brush, grasses and legumes that specifically produce diverse, high quality habitat for pollinators (Ogle et al., 2011, Keys, 2012). This has the added benefit of producing biodiverse landscapes which are a boon to CSTG, help reduce landscape fragmentation, and provide ideal habitat for wildlife (Dunn et al., 1999).

Another driver of habitat degradation and fragmentation is wildfire. Fires destroy dry habitat sagebrush and juniper, often consuming large swaths leading to succession by invasive annual grasses such as cheatgrass (Bradley et al., 2018). This pattern leads to a feedback loop:

fires destroy vegetation which often require years to decades for full recovery, leading to an increase in annual grasses that rapidly mature in burn scars and end up being problematic for propagating fires (Billings, 1994a). Uncrewed Aircraft System (UAS) monitoring techniques in post-fire habitat facilitate collection of imagery that offers a useful tool. High quality imagery can be used to create LULC maps of areas that previously burned and determine exact site-specific impacts. Further, returning to an area at regular intervals post wildfire can enable analysis of vegetation quality within areas recovering. This study focuses on one such area that burned in 2014 where the landowner has been active in reseeding portions of the burned area to enable regeneration.

4.1.1 Efficacy of Classification Models

An accurate classification is desirable to make any inference on the influence of LULC change to changing CSTG population in southeast Idaho. Often classifications of satellite imagery The literature has several comparisons of machine learning algorithms with new techniques for implementing artificial neural networking algorithms for LULC classification. A study comparing Support Vector Machines, Randon Forest, and k-Nearest Neighbor (kNN) demonstrated accuracies of 90-95% when using training data from Sentinel-2 multispectral imagery to classify LULC in the Red River Delta of Vietnam (Thanh Noi and Kappas, 2017). Another survey study of several algorithms identified the SVM algorithm as a top performer, showing accuracy as high as 90% when looking at an urban area in the Haidian District of Beijing (Qian et al., 2015). The highest accuracies (>93.5%) in image classification require a target area of at least 0.25% of the total pixel area (or 750 samples), per class (Thanh Noi and Kappas, 2017). Consistently SVM and RF are considered top contendors for high levels of accuracy in the field of image classification, but more work could be done examining environments like the sagebrush steppe.

4.1.2 Objectives

There is a long history of data collection using satellite sensors including the last 50 years of LANDSAT data, but free and publicly available satellite imagery still remains medium resolution. Currently UAS data products are generally thought of as the go to for the best resolution in field scale study areas. This chapter examines methods for data collection and processing using the MRDCS, a multispectral sensor that is easily attached to a UAS. Further, this chapter will compare the random trees and support vector machine algorithms for classification of that UAS data. Classified imagery will then be compared to similarly classified Sentinel-2 imagery. This classified data will be used to examine the vegetation in a conservation reserve program managed field, comparing the composition inside and outside the Cambridge fire boundary (2014).

4.2 Methods

4.2.1 Study Area

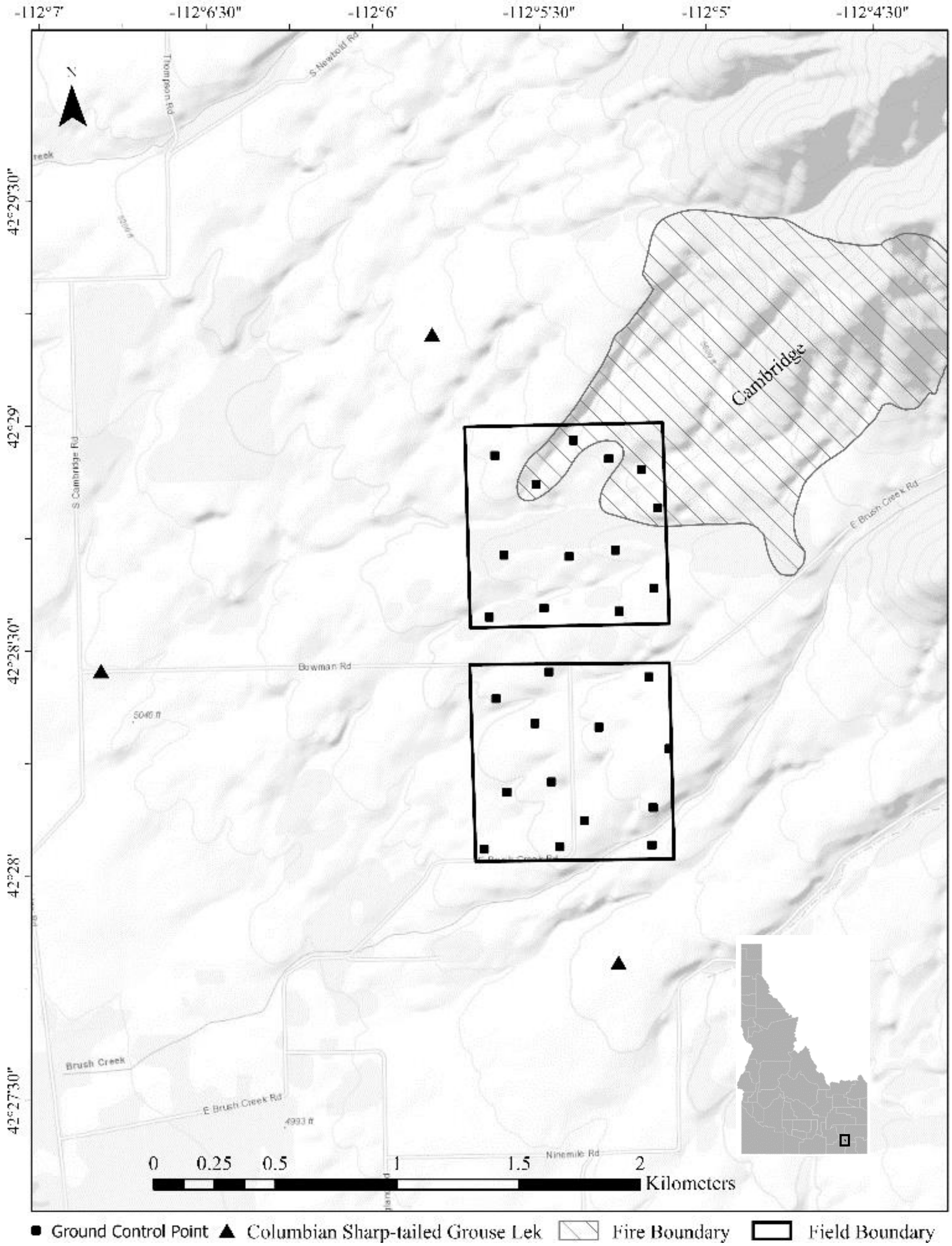

Figure 8. Conservation Reserve Program fields near Columbian Sharp-tailed grouse leks and the Cambridge wildfire (2014).

The study area was selected for its proximity to known lek locations as well as a recent wildfire. This area falls in the northeast ranges of the Great Basin physio geographic region, along the border of the Snake River Plain, east of Downey, Idaho. Each of these fields is 0.68 km^2, and are managed under the CRP starting in 2015, with the goal to provide useful habitat for pollinators, which has been found to be important for CSTG population as well. These fields contained Sainfoin (*Onobrychis viciifolia*), Yarrow (*Achillea millefolium*), blue Flax (*Linum perenne var. lewisii*), alfalfa (*Medicago sativa)*, cheatgrass (*Bromus Tectorum*), rabbitbrush (*Ericameria nauseosa*), spineless horsebrush (*Tetradymia canescens*). Also present are several stands of sagebrush in undisturbed ravines, including both big sagebrush (*Artemisia tridentata)* and threetip sagebrush (*Artemisia tripartitata)*. In 2014 the Cambridge fire burned roughly 1.5 square kilometers including the northeast corner of the study area, which has been subsequently reseeded.

4.2.2 UAS Multispectral and Optical (RGB) Imagery

Flight planning was done using the Universal Ground Control Software (UGCS) area scan tool. An excel spreadsheet was used to calculate flight factors based on the desired resulting image attributes: flight height, camera sensor size, pixel resolution, were used to determine the Ground Sampling Distance (GSD) (Figure 5). GSD and the required/desired overlap for photogrammetry of images to be stitched together was used to determine the flight speed. UGCS allows you to manage these values to plan and adjust parameters in the field based on needs

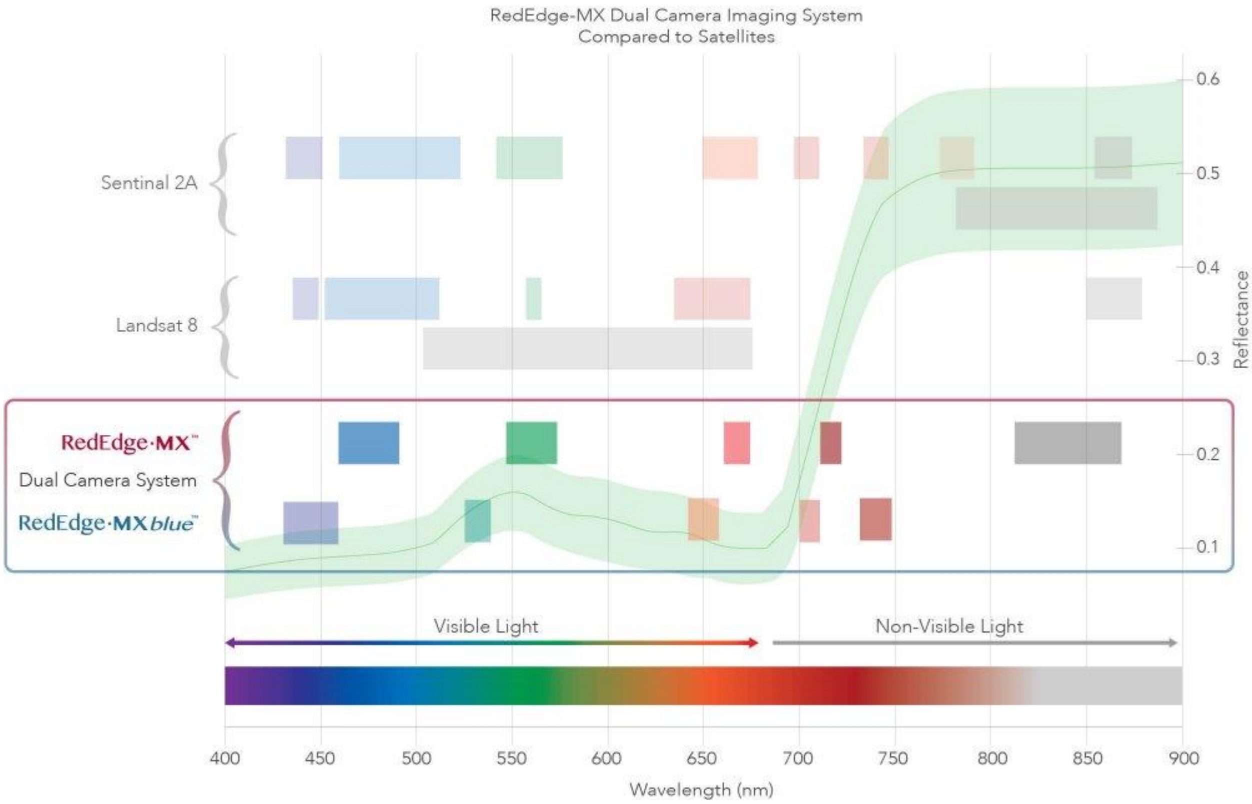

Figure 9. Spectral Band comparison between Micasense Dual Camera System and popular remote sensing satellites Sentinel-2A and Landsat 8.

which may arise based on field conditions such as wind speed or direction. We flew at 100 meters above ground level, at approximately 5 meters per second speed with 75% forward and lateral overlap between photos, with a target ground resolution of approximately 7 centimeters.

Summer, 2020 imagery used for this project was collected using the MRDCS sensor flown on a Matrice 600 Pro hexacopter. The MRDCS is a 10-band sensor that observes the same wavelengths as the Sentinel-2 MSI (Figure 9). Additional natural color imagery was collected using the Sony α6000 mirrorless camera. Settings for the camera were set to focal length of ∞, f-stop of 4, shutter speed of 1/800, and image sensor sensitivity of 100 ISO. The α6000 was set to capture images at 2 second intervals to maximize coverage area and allow overlap between images to best facilitate photogrammetry.

Sony α6000 dSLR images were geotagged using the onboard Global Navigation Satellite System (GNSS) telemetry lined up with the camera shutter time. This allowed each photograph locations to be geotagged, at approximately 3 to 5 m of error. The MRDCS images are tagged using a built in GNSS receiver, which are more accurate than the α6000 locations, in the 1 to 2 m range. To rectify this source of error, GCP locations are used as tie points to facilitate increasing the accuracy of the imagery and photogrammetry to the centimeter scale.

4.2.3 Topcon Ground Control Points

26 ground control points (GCP) were placed in the north and south fields (Figure 3), evenly distributed but spaced semi-randomly to avoid clumping and linear warping of the imagery. GCP locations were exported as a PDF and imported into Maps Avenza application to facilitate accurate placement of GCP. GCP targets were placed in the field site the morning of the first set of flights. Often vegetation obstructed planned placement of GCP, and in such cases GCP targets were placed by moving local vegetation out of the way and then staking them down as flat as possible. The use of stakes was necessary to make sure the targets were stable because there were two days of flights planned. GCP were later surveyed using the Real Time Kinematic (RTK) method for sub-centimeter levels of accuracy. Surveying the GCP targets took place over 2 trips in mid-late June of 2020.

We used the Topcon Hiper II RTK GNSS receiver for gathering survey grade coordinates. The base station was set up near the flight staging location and left to gather a continuous point while placing targets and flights. The location of the base station was marked with a stake that was flagged with pink tape for ease of finding the stake each time we set up the base station. The rover receiver connects to a Getac windows mobile device, and points are collected using the TopSURV Topo Tools application. Each target was surveyed by the rover for

60 seconds, with half second points and software enforced rover stability rules to ensure accurate points. The rover has a reported range of over a kilometer, and communication between the base and the rover was relatively stable over the entire field area. If communication ceased during the collection of a point, the TopSURV application would pause the count until a stable connection resumed. This was only an issue for points far away and behind some obstruction such as trees or a hill, but all points were collected for each GCP target.

Post correction and tying of GNSS points to the National Spatial Reference System was done using National Oceanic and Atmosphere Administration Online Positional User Service website. This requires the user to upload a logfile from the base station. The correction accounts for accounting for interference between the GNSS satellite and receiver, correction for the height of the receiver, as well as correction of errors unique to individual brands/models of GNSS receiver. We used the logfile that represented the longest continual time period spent gathering over the base station location to achieve the most accurate results. The Topcon Tools software was used to change the base station location to the corrected value, and the correction is applied to all RTK connected locations. Points were exported as a CSV including latitude, longitude, and altitude values for all GCP.

4.2.4 Image Processing

We aligned the UAS imagery from both the Sony and Micasense sensors using Agisoft Metashape Professional. Images generated by the Sony α6000 required preprocessing in the form of color balance and correction using Adobe Lightroom. Image brightness was generally increased, and color balancing via histogram manipulation to color match images from multiple flights match. Processed Sony images were imported into Agisoft corresponding chunks. Initial batch alignment was performed in Agisoft to create a rough model of each chunk, tying image locations to their geotagged locations and aligning matching pixels on overlapping images. This allows for the placement of GCP markers to targets located in the imagery. The OPUS corrected GCP values were brought in to Agisoft and placed on targets within the imagery to improve georeferencing.

4.2.5 Image Classification

Imagery collected by UAS was used to create a large scale, species level classification maps via the SVM and RF models. The classification tools Support Vector Machine (SVM) and Random trees are available to classify imagery within ArcGIS Pro 2.7. ArcGIS classification wizard takes training samples and segmented images and produces a high-quality classification depending on the model used. Applying the workflow using two models allowed creation of two classification maps within the same program, using the same training data. The workflow for ArcGIS for supervised classification using object-based methodology requires regions of interest and a segmented image. Regions of interest were created to represent each class; in this case, sage, shrub, herbaceous, annual herbaceous, litter and bare ground. These classes were chosen to match the RSC dataset. A segmented image is created in the wizard by clustering similar pixels together, and takes into account object shape and similarity when producing an output. The training data and segmented image are fed into the classification wizard which outputs a classified image and metrics regarding precision and accuracy of classification (Figure 11. Classification map of fields north and south of Bowman Road near Downey, Idaho. Support Vector Machines (SVM) classification of multispectral imagery from MicaSense Dual Camera System. Classification accuracy in north 0.79, south 0.89.

4.3 Results

4.3.1 Maps

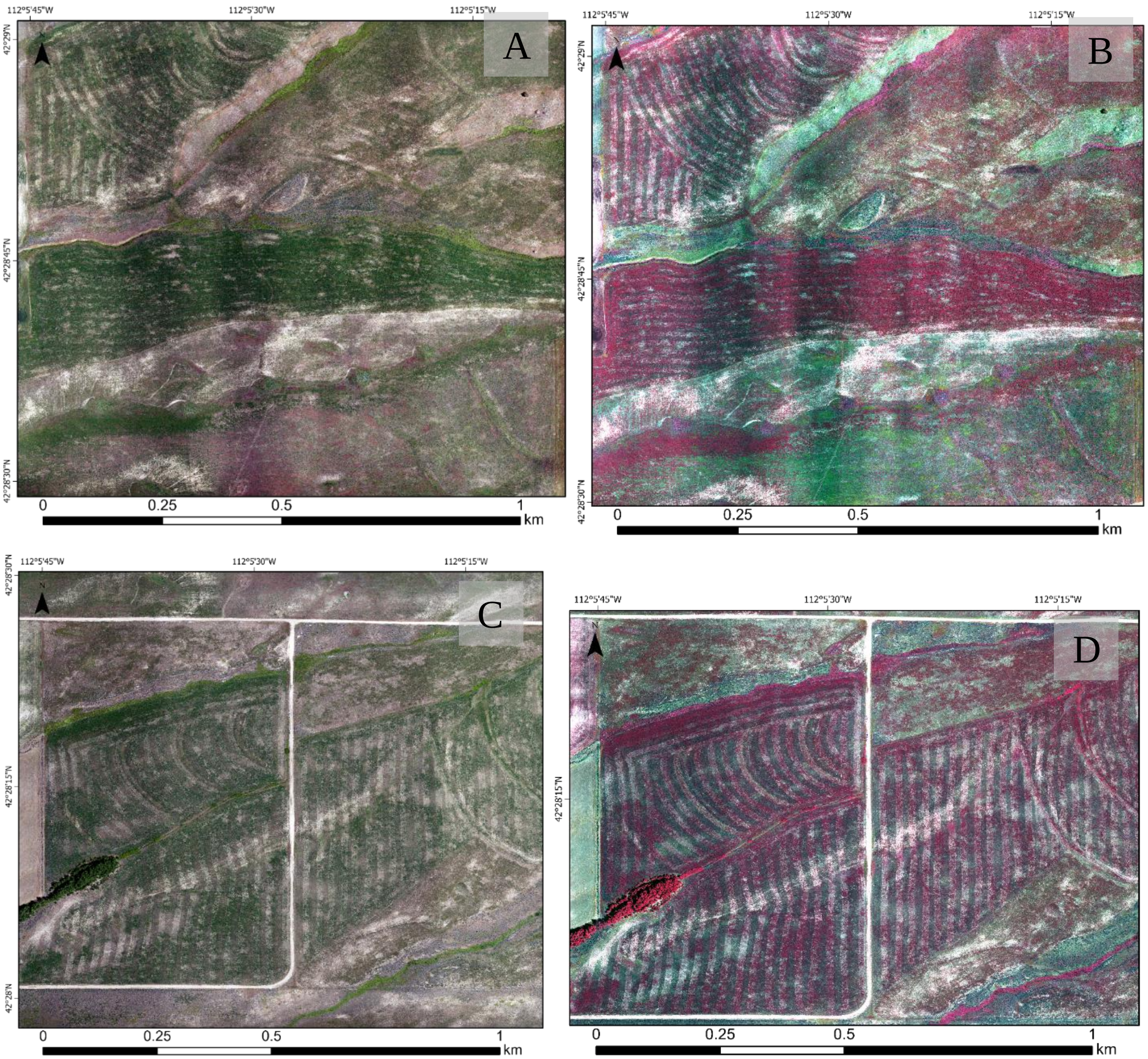

Figure 10. Orthoimagery of Fields north and south of Brush Creek and Bowman Roads, collected using DJI Matrice 600 hexacopter. False color Composite image from Micasense Dual Camera System 10 band multispectral sensor, and true color imagery from Sony α6000 mirrorless camera. Orthoimages created using Agisoft Metashape Professional. A & B show north field, C & D show South Field. False color shows bands red – (red 650 nm), green – (red edge 716 nm), blue – (green 560 nm), used to visually differentiate several varieties of plant.

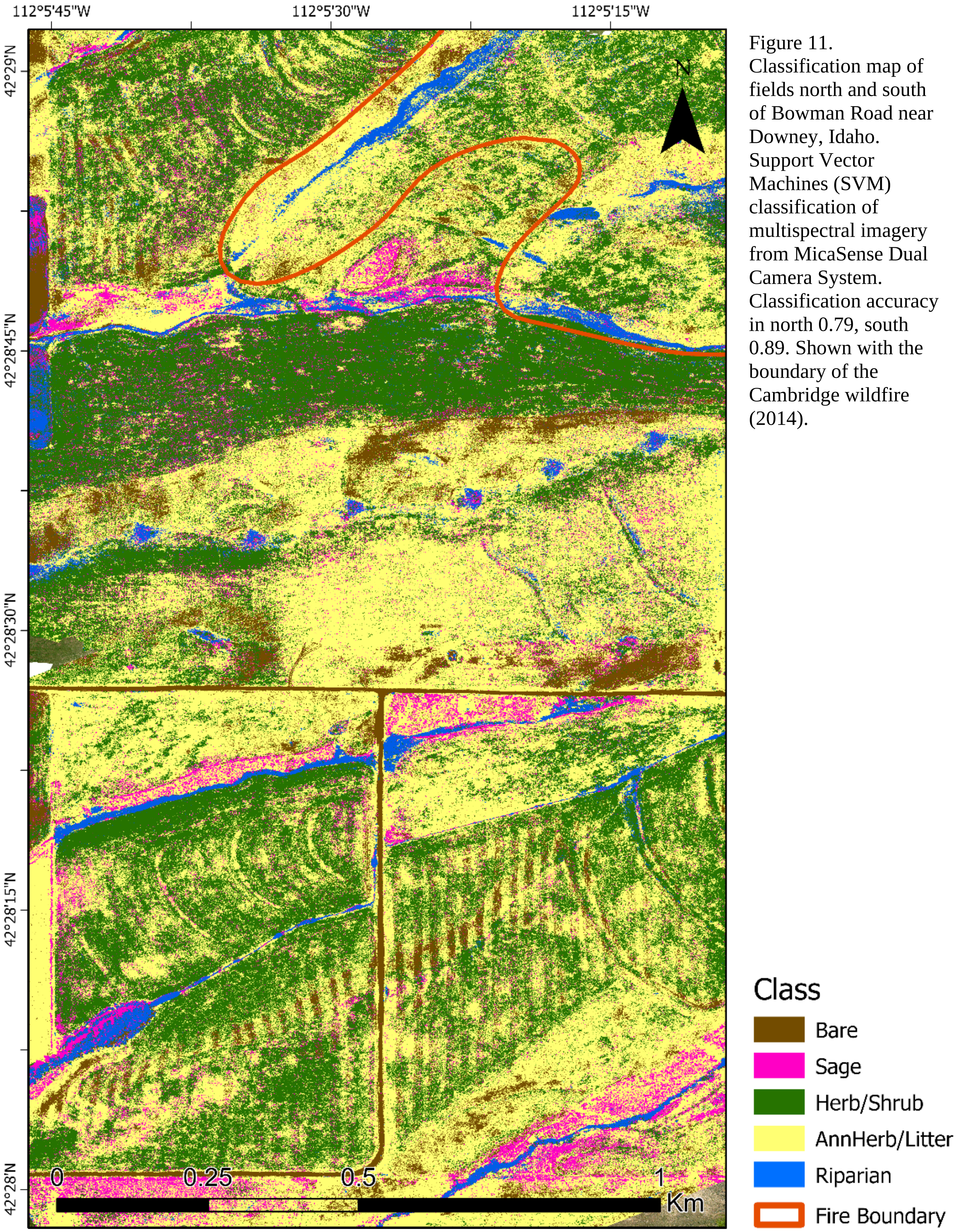

Figure 11. Classification map of fields north and south of Bowman Road near Downey, Idaho. Support Vector Machines (SVM) classification of multispectral imagery from MicaSense Dual Camera System. Classification accuracy in north 0.79, south 0.89. Shown with the boundary of the Cambridge wildfire (2014).

4.3.2 Classification Confusion Matrices

Confusion matrices were calculated using 699 validation points for the north field and 544 validation points for the south field (Table 5). All points were not used in training the classification. Classification accuracy for the south field, using the SVM algorithm was 0.893, with a kappa value of 0.866. The accuracy of the random trees (RT) algorithm was calculated as 0.840, with a kappa value of 0.799 for the same field. The classification of the north portion of the study area showed an accuracy of 0.798 and kappa value of 0.734 for SVM; 0.840 accuracy and 0.799 kappa using RT. Finally, SVM classification of the same area using Sentinel-2 multispectral resulted in an overall accuracy of 0.439 and 0.454 and kappa value of 0.299 and 0.302 using the same validation points.

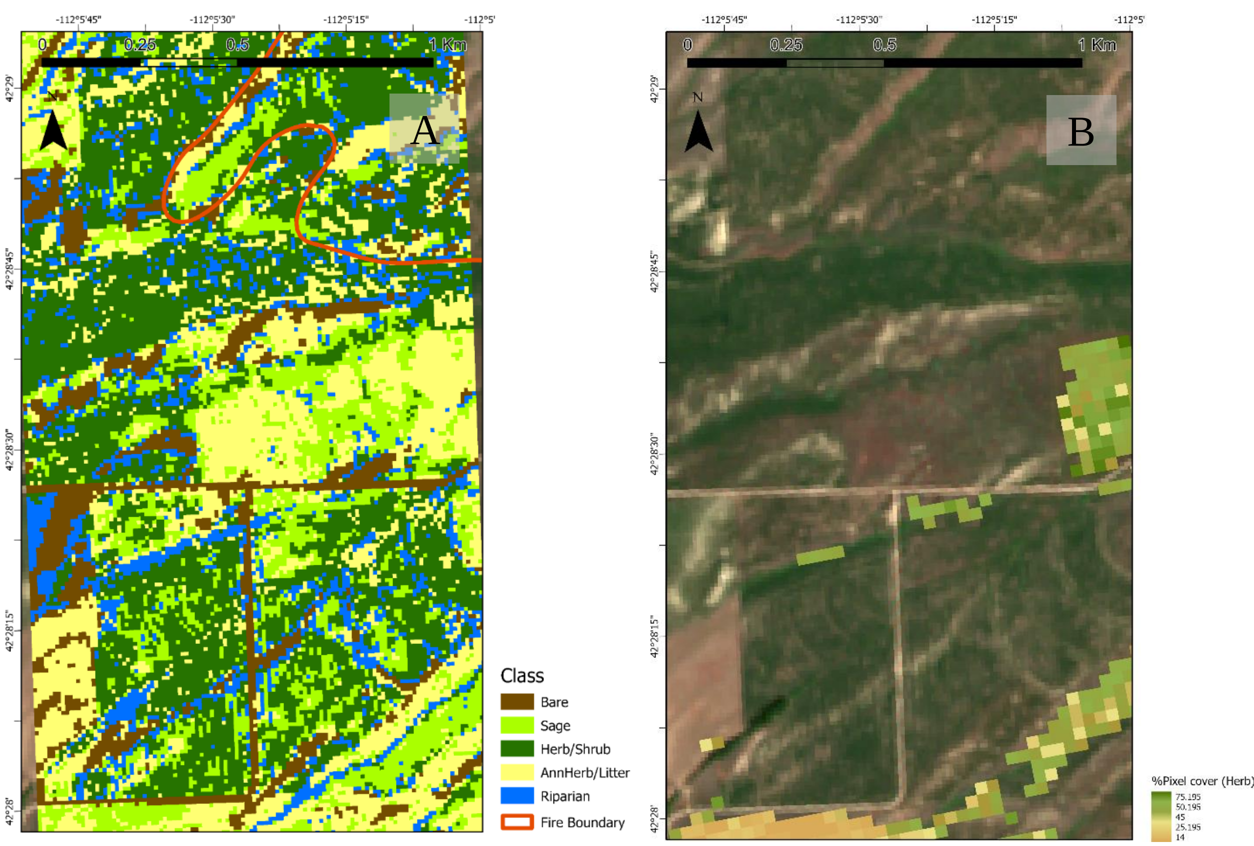

Figure 12. A SVM Classification of Sentinel-2 imagery. B is map of RSC herb % cover for the area over Sentinel-2 base imagery.

Table 5 - Confusion Matrix Comparison (Random Trees and Support Vector Machine) of various classification algorithms used to classify fields near Bowman and Brush Creek Roads near Downey, Idaho. U(ser) Accuracy assesses false positives, and p(roducer) accuracy assesses false negatives.

UAS Random Trees - North	Bare	Sage	Herb / Shrub	AnnHerb / Litter	Riparian	Total	U Accuracy	Kappa
Bare	74	1	1	7	1	84	0.881	0
Sage	5	96	11	26	1	139	0.691	0
Herb / Shrub	0	2	87	5	2	96	0.906	0
AnnHerb / Litter	28	11	16	202	1	258	0.783	0
Riparian	1	4	39	13	65	122	0.533	0
Total	108	114	154	253	70	699	0	0
P Accuracy	0.685	0.842	0.565	0.798	0.929	0	0.7496	0
Kappa	0	0	0	0	0	0	0	0.674
UAS Support Vector Machine - North	Bare	Sage	Herb / Shrub	AnnHerb / Litter	Riparian	Total	U Accuracy	Kappa
Bare	82	0	1	10	0	93	0.882	0
Sage	9	94	7	17	2	129	0.729	0
Herb / Shrub	0	4	108	8	1	121	0.893	0
AnnHerb / Litter	17	16	24	210	3	270	0.777	0
Riparian	0	0	14	8	64	86	0.744	0
Total	108	114	154	253	70	699	0	0
P Accuracy	0.759	0.825	0.701	0.83	0.914	0	0.798	0
Kappa	0	0	0	0	0	0	0	0.734
UAS Random Trees - South	Bare	Sage	Herb / Shrub	AnnHerb / Litter	Riparian	Total	U Accuracy	Kappa
Bare	99	0	1	7	0	107	0.925	0
Sage	3	110	16	34	2	165	0.667	0
Herb / Shrub	0	0	77	0	14	91	0.846	0
AnnHerb / Litter	0	2	3	79	1	85	0.929	0
Riparian	0	1	3	0	92	96	0.958	0
Total	102	113	100	120	109	544	0	0
P Accuracy	0.971	0.973	0.77	0.658	0.844	0	0.84	0
Kappa	0	0	0	0	0	0	0	0.799
UAS Support Vector Machine - South	Bare	Sage	Herb / Shrub	AnnHerb / Litter	Riparian	Total	U Accuracy	Kappa
Bare	99	0	0	13	0	112	0.884	0
Sage	1	109	9	11	3	133	0.82	0
Herb / Shrub	0	2	80	2	2	86	0.93	0
AnnHerb / Litter	2	2	5	94	0	103	0.913	0
Riparian	0	0	6	0	104	110	0.945	0
Total	102	113	100	120	109	544	0	0
P Accuracy	0.971	0.965	0.8	0.783	0.954	0	0.893	0
Kappa	0	0	0	0	0	0	0	0.867

Sentinel Support Vector Machine - South	Bare	Sage	Herb / Shrub	AnnHerb / Litter	Riparian	Total	U Accuracy	Kappa
Bare	52	10	3	10	4	79	0.658	0
Sage	8	39	12	37	2	98	0.398	0
Herb / Shrub	12	4	65	30	25	136	0.478	0
AnnHerb / Litter	8	54	11	26	21	120	0.217	0
Riparian	22	6	9	17	57	111	0.514	0
Total	102	113	100	120	109	544	0	0
P Accuracy	0.51	0.345	0.65	0.217	0.523	0	0.439	0
Kappa	0	0	0	0	0	0	0	0.299
Sentinel Support Vector Machine - North	Bare	Sage	Herb / Shrub	AnnHerb / Litter	Riparian	Total	U Accuracy	Kappa
Bare	39	3	3	20	2	67	0.582	0
Sage	7	54	15	61	12	149	0.362	0
Herb / Shrub	16	31	93	60	10	210	0.443	0
AnnHerb / Litter	24	17	23	93	8	165	0.564	0
Riparian	22	9	20	19	38	108	0.352	0
Total	108	114	154	253	70	699	0	0
P Accuracy	0.361	0.474	0.604	0.368	0.543	0	0.454	0
Kappa	0	0	0	0	0	0	0	0.302

P accuracy shows the accuracy of how many points were classified correctly of a given class, where u accuracy shows the accuracy of those points with known control classes (Table 5). In the northern field the two class pairs most often confused were herb / shrub with riparian, and bare ground with annual herbaceous with litter. Herb/shrub was accurately predicted at 89.3% (SVM) and 90.6% (RT) of control points. RT overpredicts herbaceous area as riparian 24.7%, and SVM overpredicts litter / annual herbaceous 15.6%. The classifications also had trouble distinguishing litter / annual herbaceous cover from bare ground, with 25.9% (RT) and 15.7% (SVM) false predictions. Confusion between LULC classes was similarly demonstrated in the SVM algorithm but to a lesser degree, with only 15% of false predictions. The kappa coefficient for RT was 0.67 in the north and 0.79 in the south. SVM models performed better in their respective fields, at 0.73 in the North, and 0.86 in the south.

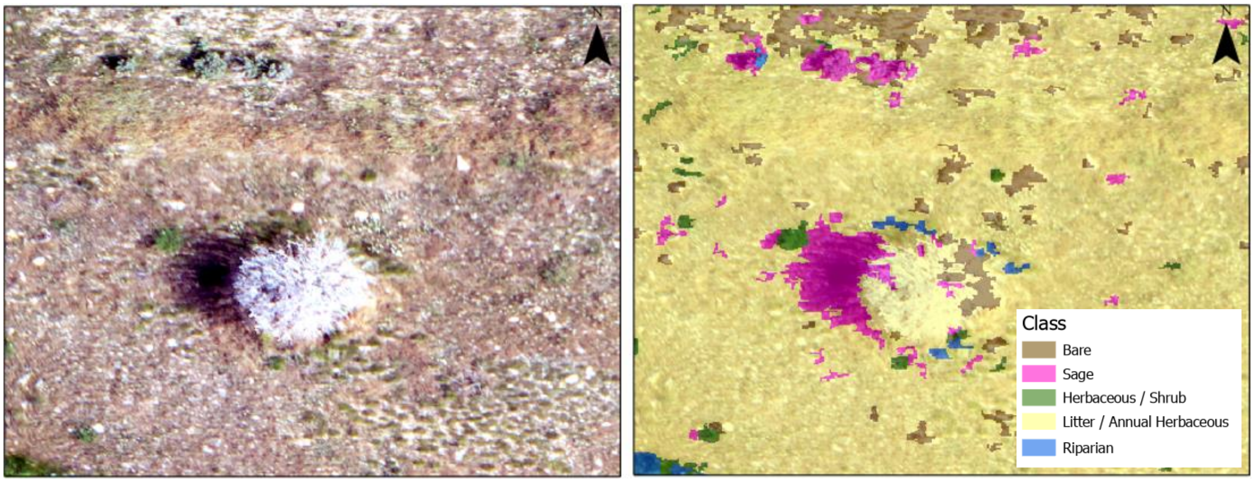

Figure 13. Burned sagebrush comparison from Sony α6000 orthoimage and SVM Classification.

4.3.3 Comparison of vegetation composition

Classified MRDCS imagery was used to examine the land cover composition inside and outside the Cambridge fire perimeter (We found varying levels of difference within the land cover for all classes. The largest increase within the fire perimeter represented litter/annual herbaceous combined land cover, at +14.41%, which includes many areas of burned sagebrush husks, and cheatgrass in various lifecycle stages (Figure 13). The next largest increase was riparian, at +4.92%. The largest negative difference was the combined herb/shrub, which had -12.59% less herb/shrub cover inside the fire boundary compared with outside. We found a decrease in sage cover within the fire perimeter of -4.78% and decrease in bare ground by -1.95%. Classified imagery from Sentinel-2 found much less change, generally within 0-3% for

Table 6. Land cover comparison within area burned in 2014 Cambridge Fire and rest of fields.

	Micasense Burned	Micasense CRP	Micasense Difference	Sentinel Burned	Sentinel CRP	Sentinel Difference
Bare	0.041	0.060	-1.95	0.076	0.091	-1.78
Sage	0.034	0.082	-4.78	0.185	0.196	-1.43
Herb/Shrub	0.284	0.410	-12.59	0.415	0.394	2.29
AnnHerb/Litter	0.557	0.413	14.41	0.209	0.201	0.967
Riparian	0.085	0.036	4.92	0.116	0.116	-0.059

We found varying levels of difference within the land cover for all classes. The largest increase within the fire perimeter represented litter/annual herbaceous combined land cover, at +14.41%, which includes many areas of burned sagebrush husks, and cheatgrass in various lifecycle stages (Figure 13). The next largest increase was riparian, at +4.92%. The largest negative difference was the combined herb/shrub, which had -12.59% less herb/shrub cover inside the fire boundary compared with outside. We found a decrease in sage cover within the fire perimeter of -4.78% and decrease in bare ground by -1.95%. Classified imagery from Sentinel-2 found much less change, generally within 0-3% for all classes.

4.4 Discussion

4.4.1 Discussion of UAS Imagery and Classifications

Imagery and maps created using photogrammetry techniques illustrate a fine scale resolution of 7.5 cm, which is useful for the ability to resolve individual plants in the field area with high accuracy to ground control points and inform the classification model. The classification model performed better for some classes than for others. False positives and false negatives (U and P Accuracy in Table 5) in the confusion matrix give some insight into how the classification algorithm is operating. The RT classification shows under classification of riparian, often mistaken as herb/shrub. This is because the riparian vegetation in the northern field contains tall grasses which are spectrally similar to leafy herbaceous and shrub plants, as opposed to the woody plants found in the southern area, such as willow. The SVM model has a higher accuracy. Herb/shrub is the most overclassified for the north field, often misclassified rom riparian and annual herbaceous covers. In the south field sage was often classified as annual herbaceous / litter classes. This is because the sage stands in the southern field tend to be darker with visible wood patches (Figure 14A), which are spectrally similar to dead vegetation outlined as litter.

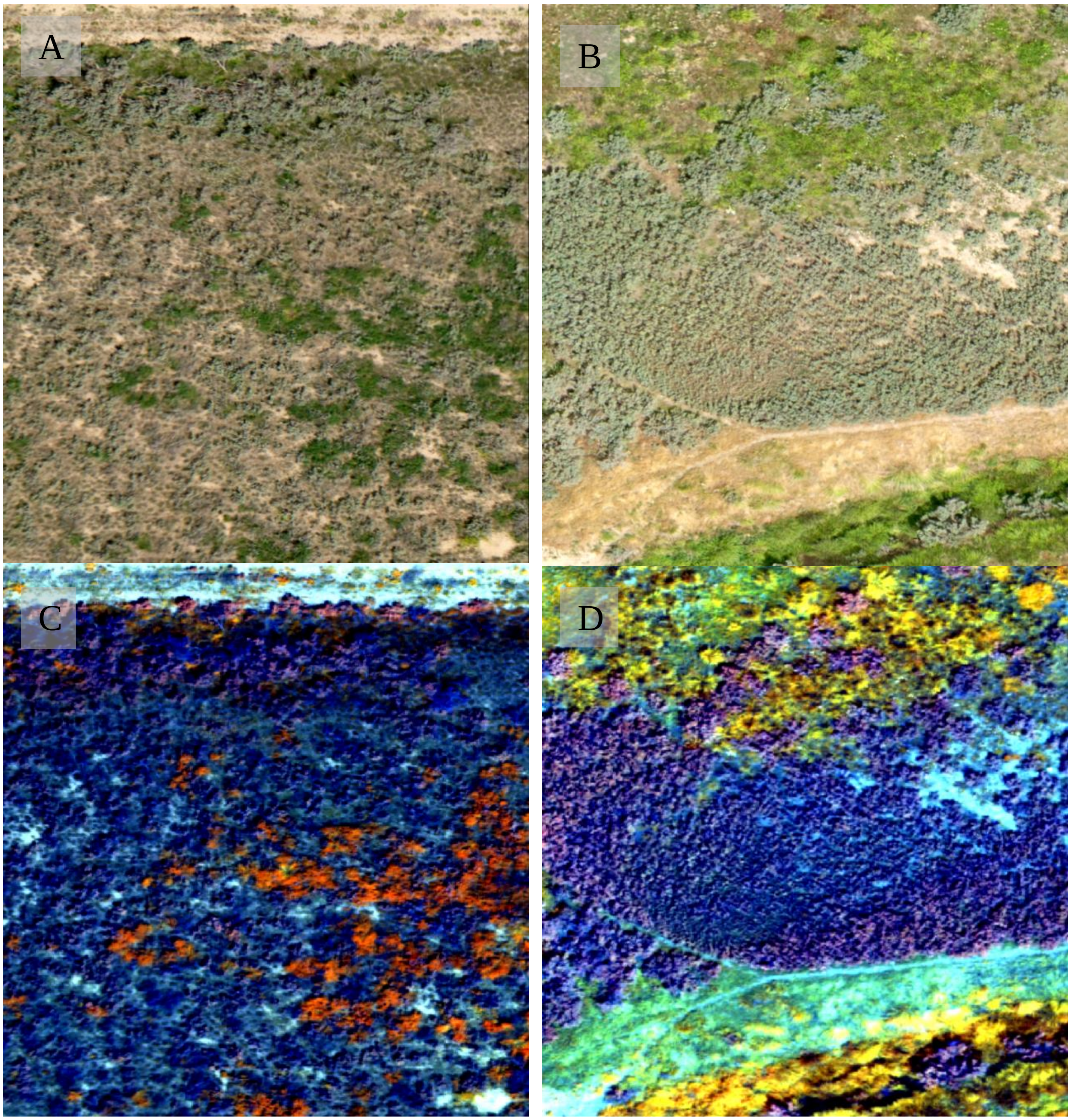

Figure 14. Visual comparison of images of sagebrush in true and false color composite (Rededge 705 nm, Red 650 nm, Blue 475 nm). A & C show location in South Field, B & D Show North Field. Comparison of these images reveals sage in the north (B&D) covered with leafy material, whereas in the south (A&C) more wood material is visible.

We compared vegetation in and outside of the Cambridge fire boundary (Table 6). One interesting difference was the increase in Riparian vegetation inside the fire boundary. This may be topologically controlled; riparian vegetation grows along drainages in the valley lows where the fire appears to have burned further southwest. Within the fire perimeter there are clusters of riparian vegetation in flat and wide areas of the northeast. These areas were soggy even in July during ground flag placement, and it is possible that increased moisture could have mitigated fire damage to these isolated locations. There is also evidence that riparian species are able rapidly regrow in a post fire environment when subjected to the same levels of precipitation (Reeves et al., 2006). One key difference to note is the presence of more willow and other woody structure in the overstory of the riparian areas of the south field that were not subjected to fire. This study only examined Sentinel-2 from before the fire, which was too coarse resolution to determine species change. Older aerial photography may be useful to differentiate those species.

The Sentinel-2 classification (Figure 12A) had low overall accuracy for both fields, 44% (south) and 45% (north), due to the overall low-resolution of the classification with respect to the validation dataset (Table 5 sections 5 & 6). Validation points were created using multispectral imagery from the MRDCS which has 7-cm resolution, and Sony RGB imagery which has a 3-cm resolution. The resolution of Sentinel-2 is more than 100 times larger, 10-m, often containing validation points of different classes within the same Sentinel-2 pixel. The best accuracy result of the Sentinel-2 classification was of bare ground at 65% (south) and 58% (north); but bare ground was also massively overpredicted making up nearly 64% of false negatives in the north field and 49% in the south. The RSC dataset was also examined for this study area, but were inconclusive due to sparse coverage (Figure 12B).

Chapter 5. Conclusion

Southeastern Idaho's healthy sagebrush-steppe is vital habitat for CSTG lekking, nesting and brood rearing. This research found strong correlation between leks with positive population trends and increased CRP area, burned area, the sage cover trend, as well as the trend in shrub cover. High amounts of burned area which often translated to negative sage and shrub trends correlated with declining lekking population trends in proximate areas. The model we found that performed best was the single variable CRP area. CRP area had the lowest value Akaike information criterion, meaning that the least amount of information was lost from modeling the population. Future research should examine habitat quality of CRP to determine the relationship beyond presence. If there is interest the methods used for this paper could be used to assess other areas of conservation effort beyond CRP, or be applied to other species. Additionally, measurements of wildfire severity normalized to a set time period could be assessed per fire to examine the relationship beyond the binary of disturbed versus undisturbed land. Denser temporal coverage of CSTG of lek counts (more and more often) should facilitate analysis of how LULC change impacts lekking population in the short term.

Modeled satellite imagery like the RSC dataset offers a useful tool for habitat analysis. The RSC model for sage trend correlates well enough with fire area that multivariable analysis had warnings for collinearity, which seems to validate the sage cover model. While the RSC dataset was useful for regional scale analysis, it fell short during examination at the field scale just due to the lack of coverage within the mask layer. The downfall of Sentinel-2 imagery for this area is the very small study area to pixel size ratio, which limits the number of training polygons it is possible to use. Likewise, a 10 m^2 pixel typically contains more than one LULC class which means the spectral signature for smaller objects are mixed together. The 1 km^2 (or less) field size is a more reasonable area to use UAS for data collection, and facilitates high quality image processing. Methods used for this research seem broadly applicable for future projects, including recommendations for flight planning, ground control placement, and image processing using the Micasense Rededge Dual Camera System multispectral sensor. Future work should facilitate super resolution of 10 m^2 pixel via a fusion product of UAS and satellite imagery. Collection and comparison of UAS imagery and Sentinel-2 brings us a step closer to data fusion products which can be invaluable for time series analysis.

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Additional Datasets

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