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The effect of vegetative structure on nest-burrow selection by the Western Burrowing Owl: Comparing traditional methods to photogrammetry with an Unmanned Aerial System

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THE EFFECT OF VEGETATIVE STRUCTURE ON NEST-BURROW SELECTION BY THE WESTERN BURROWING OWL: COMPARING TRADITIONAL METHODS TO PHOTOGRAMMETRY WITH AN UNMANNED AERIAL SYSTEM

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PREFACE

This thesis is written in the style of the Transactions of the Kansas Academy of Science, to which a portion will be submitted for publication.

ABSTRACT

The shortgrass prairie ecoregion in the United States has been reduced to 52% of its historical extent, contributing to reduced habitat for native species. One such species is the Burrowing Owl (*Athene cunicularia*). The Western Burrowing Owl subspecies (*A. c. hypugaea*) is listed as a Species of Special Concern in nearly every western and midwestern state, including Kansas where it is designated as a Tier II Species of Greatest Conservation Need. Habitat destruction due to conversion to cropland, increasing use of pesticides, and reduction in burrowing mammal abundance are the primary threats that have led to this status. The objectives of my study were to determine if vegetative structure affected Burrowing Owl nest-burrow selection and to determine if UAS imagery could be used to efficiently and effectively quantify vegetative structure.

Vegetative structure and its effect on burrow selection in Burrowing Owl was measured in two ways. First, structure was quantified with an elevated Daubenmire cover classification scheme. Subsequently, I quantified structure with a photogrammetric technique in which aerial imagery acquired with the aid of an unmanned aerial system (UAS) was used to generate three-dimensional models of the vegetation. Vegetation surrounding both occupied and unoccupied burrows was classified by establishing four 20-m transects oriented to each cardinal direction and centered at the burrow opening. Along each transect, a 1-m x 1-m Daubenmire frame was used to classify vegetation at 2 m, 5 m, 10 m, and 20 m from the burrow. A DJI Phantom 4 Pro was flown over each burrow to collect a series of overlapping images. With the imagery from the UAS, three-dimensional models of vegetative structure were generated. Visual obstruction by vegetation was estimated with these models. Burrowing Owl presence increased with bare ground cover ($Z = 2.29$, $df = 23$, $p = 0.022$) and decreased with forb cover ($Z = -2.54$, $df = 23$, $p = 0.011$). Unoccupied burrows had significantly more obstruction than occupied burrows ($X^2 = 266$, $df = 9$, $p < 0.001$). The results of my study suggest that imagery collected by UAS can be used as an effective and efficient method of characterizing vegetative structure and significantly reduce the amount of time and money required to evaluate wildlife and habitat.

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First, I thank my wife Darrah for the support she gives me every day. She has not only provided emotional support throughout my time at Fort Hays State University but has lent her own scientific expertise in the field and in helping to edit this thesis. Next, I thank my awesome mom, Shiela. She raised my brother and me on her own and raised us to care about the world in which we live, and for me that has manifested in a care for how we treat the earth and its organisms. I also thank my brother, Mason, for always being there for me when I wanted to escape the stress of school and thesis work by talking about football, our shared love of music, Doctor Who, and playing board games.

I thank all the members of my thesis committee (Dr. Stark, Dr. Channell, Dr. Finck, Dr. Greer, and Matt Bain) for the time they sacrificed to help me make my thesis the best it could possibly be. Specifically, I thank Dr. Channell. When I first came to Fort Hays to finish my undergraduate degree, he was just Darrah’s professor. He became my undergraduate advisor and helped shape the way I question the world around me so that I could hopefully apply my findings now and in the future to biodiversity at large scales. I also specifically thank Matt Bain. Matt hired me as a summer intern at Smoky Valley Ranch in 2016, and, without that job, I would not have had the idea for my thesis project, the experience with the land necessary to find owls as quickly as I did, or have learned some of the most important management and conservation practices for grassland ecosystems. Also, without Matt and The Nature Conservancy, I would not have had the fantastic research site that just happened to also come with a free bed.

I thank my graduate advisor Dr. Stark. From the first conversation we had about the potential project I wanted to do for this thesis, I knew it was going to be the most fun and challenging thing I had ever done. Dr. Stark never pushed me farther than he thought was necessary but gave me the space to push myself more than I ever have before. I come out of this thesis project with more knowledge and a better ability to express that knowledge than I could have ever expected.

I could not have completed this research without the funding I received from both the Kansas Ornithological Society and Kansas Academy of Sciences. The funding went toward traveling to Smoky Valley Ranch, food while I did fieldwork at the ranch, and the equipment I needed to complete my fieldwork.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

INTRODUCTION

Grasslands cover 4.6 billion ha of land and contain 24% of the vegetation on Earth (Sims and Risser 2000). These areas receive enough precipitation to support grasses, but the available water in the soil is not sufficient to support trees. Although closely correlated to mean annual temperature and precipitation, grassland net primary productivity ranges from 100-1700 $g/m^2/yr$ (Lauenroth 1979). At the high end, grassland productivity is comparable to even the most productive biomes, e.g. 1200 $g/m^2/yr$ in some tropical rainforests (Martinez Yrizar et al. 1996).

In the United States, grasslands cover about 300 million ha (Sims and Risser 2000) and are responsible for between 100-700 $g/m^2/yr$ of net primary productivity (Sala et al. 1988). However, grassland areas have been significantly reduced since European colonization. From 1850–1990, 287.2 million acres of grassland west of the Mississippi River were converted, primarily to cropland (Conner et al. 2001).

The range of the shortgrass prairie ecoregion has been reduced to 52% of its historical extent (Samson et al. 2004), contributing to reduced habitat for several animal species. The range of the black-tailed prairie dog (*Cynomys ludovicianas*), one of the most negatively affected species, has declined from 30 million ha 200 years ago to 0.5–0.8 million ha today (Proctor et al. 2006). The black-tailed prairie dog is a keystone species in shortgrass ecosystems. They clip vegetation, which allows several bird species to survive in the shorter grass (Agnew et al. 1986), and prairie dog burrows provide habitat for hundreds of species.

The Burrowing Owl (*Athene cunicularia*) is one such species that benefits from prairie dogs. Burrowing Owl presence and density are directly linked to prairie dog presence and density (Desmond et al. 2000). Burrowing Owls nest in abandoned prairie dog burrows in areas of early plant succession (MacCracken et al. 1985). The Western Burrowing Owl subspecies (*A. c. hypugaea*) is a grassland specialist, with a distribution encompassing most of western North America (Figure 1; Klute et al. 2003). This subspecies has been listed as a Species of Special Concern in several western and midwestern states (Sheffield 1997), including Kansas where it is designated as a Tier II Species of Greatest Conservation Need (Rohweder 2015). Habitat conversion to cropland, increased use of pesticides, and reduction in burrowing mammals are the primary threats that have led to this designation (Klute et al. 2003).

In the face of these threats, it is essential for the conservation and management of the Western Burrowing Owl that we understand its habitat preferences in areas where the species continues to succeed. The Smoky Valley Ranch in Logan County, Kansas is one such area. The ranch has 1600 ha of habitat managed, in part, for black-tailed prairie dogs. Migratory Burrowing Owls breed and rear nestlings on the property. This habitat is being encroached upon by a native, warm-season grass, purple three-awn (*Aristida purpurea*). Black-tailed prairie dog and Burrowing Owl densities have been reduced as a result.

Habitats like shortgrass prairies have traditionally been quantified with on-the-ground protocols that require hours of data collection. For example, McCracken et al. (1985) used a standard Daubenmire frame and canopy cover classification scheme to establish four 20-m transects centered on occupied and unoccupied burrows, one at each cardinal direction. The authors reported that the vegetation within the first 5 m of the burrow was significantly different between occupied and unoccupied burrows. However, the vegetative cover classes at 6–10 m and 11–20 m from the burrow did not differ between occupied and occupied burrows. Even with extensive fieldwork, this study was unable to produce a fine-scale description of the role of vegetative structure in Burrowing Owl nest selection. In recent years, collection of vegetative structure data has been undertaken by remote sensing, and advances in unmanned aerial system (UAS) technology hold great promise.

Unmanned aerial systems have a sensor, a vehicle on which the sensor is carried, and some form of ground control station to provide spatial data to the UAS. More advanced UAS have onboard global positioning (Colomina and Molina 2013).

The potential of UAS for photogrammetry and remote sensing has been understood since the early 1980s when radio-controlled platforms integrated with navigation and mapping sensors were used to collect high-resolution imagery at low altitudes (Wester-Ebbinghaus 1980). Subsequently, UAS have expanded exponentially. In 2005, the number of UAS referenced by Unmanned Vehicle Systems International was 544. By 2013, this number had increased to 1708. Most UAS were developed for and used by military entities; however, their use in other applications has grown considerably. Military entities made up 73% of the referenced UAS in 2005 but fell to 33% in 2013. The fastest growing applications are in civilian and commercial enterprises that require precise spatial information that has traditionally been costly or time consuming to obtain, e.g. surveying and construction management. The increase in UAS development, manufacturing, and use by a variety of disciplines has resulted in substantial economic effects worldwide. The global market revenue of UAS was 5,400 M€ (6,131,727,000 USD) in 2013 and was estimated to rise to 6,350 M€ (7,210,456,750 USD) by 2018 (Colomina and Molina 2013).

In both agriculture and environmental monitoring, the use of UAS is rapidly expanding. Monitoring global biodiversity and the health of row crops have traditionally been accomplished by the use of large, expensive sensors deployed on manned aircraft or satellites. Unmanned aerial systems provide a more flexible and inexpensive alternative (Colomina and Molina 2013). The primary benefit of UAS in agricultural and environmental applications is the replacement of substantial portions of costly and time-consuming on-the-ground data collection. These quantitative spatial data are assembled through the same photogrammetric methods used to process satellite or other imagery.

The type of photogrammetry used in my study involves mounting a downward-facing camera to an aircraft, capturing multiple overlapping photographs (Appendix 1), and processing the photographs with computer software (Appendix 2). Three-dimensional structure of vegetation or other surface features can then be modeled from densified point clouds (Appendix 2). The primary use of these three-dimensional models has been for quantifying the height of agricultural crops to predict yield and biomass (Grenzdörffer 2014).

In addition to monitoring crops and quantifying their vertical structure, UAS have been used to monitor wildlife and habitat conditions. Conserving natural resources requires consistent monitoring so management decisions can be made. Monitoring populations of relatively large organisms often requires expensive, logistically difficult aerial surveys with manned aircraft or satellites. Manned aircraft surveys often require funds from external sources, which are inconsistent (Dunham 2012). Aerial surveys from manned aircraft are also dangerous for the operators (Jones 2003, Sasse 2003, Wilkinson 2007, and Watts et al. 2010). Imagery acquired by satellites provides relatively high-resolution imagery, which can be used to monitor large areas of habitat and large organisms such as ungulates or aquatic mammals. However, satellite imagery is expensive, susceptible to cloud cover (Loarie et al. 2007), and cannot detect smaller organisms or fine-scale changes in habitat.

Compared to manned aerial surveys and satellite imagery, UAS collect data with high spatial and temporal resolution (Xiang and Tian 2011, Westoby et al. 2012), fly below cloud cover (Jones et al. 2006, Xiang and Tian 2011), and are relatively safe for the operators (Jones et al. 2006, Watts et al. 2010). Unmanned aerial systems are smaller, less expensive, and provide higher spatial resolution. These systems have been used to count organisms that would be too small to detect with satellite or aerial imagery (Wich and Koh 2012 and Grenzdörffer 2013), to calculate Normalized Difference Vegetation Indices (NDVI, Bendig et al. 2012), to classify trees to species (Gini et al. 2012), and to monitor stream temperatures (Jensen et al. 2012). One of the most important benefits of satellite and UAS imagery is that the imagery provides systematic and permanent records that can be assessed by other researchers when new or improved techniques are developed (Hodgson et al. 2013). These records provide a snapshot of the system at the time of data collection that is not preserved in data collected with traditional methods.

The objectives of my study were to determine if vegetative structure affected Burrowing Owl nest-burrow selection and to determine if UAS imagery could be used to efficiently and effectively quantify vegetative structure. I quantified vegetative structure with two methods, an elevated Daubenmire vegetative cover classification scheme and with a photogrammetric technique in which aerial imagery acquired by a UAS was used to generate three-dimensional models of the vegetation. I predicted that occupied burrows would have reduced vegetative structure compared to unoccupied burrows as quantified by both methods.

METHODS

Study Area

The Smoky Valley Ranch (SVR) is a Nature Conservancy property in Logan County, Kansas that comprised 7290 ha at the time of my study (Figure 2). The primary management regime is cattle (*Bos taurus*) grazing in a rotational pattern between April and October each year. In addition to cattle, vegetation is also grazed by a herd of American bison (*Bison bison*) and by black-tailed prairie dogs. Vegetation is also influenced by the historic absence of fire, drought, and invasive species. Invasive and encroaching species include woody plants such as salt cedar (*Tamarix spp.*), Russian olive (*Elaeagnus angustifolia*), eastern redcedar (*Juniperus virginiana*), and Siberian elm (*Ulmus pumila*). The herbaceous invasive and encroaching species that occur on the ranch include purple three-awn, musk thistle (*Carduus nutans*), and bind weed (*Convolvulus arvensis*; Bain 2016).

Smoky Valley Ranch occurs in the central shortgrass prairie (Bain 2016). The shortgrass prairie ecoregion is classified by a relatively long growing season, sparse precipitation, and higher summer temperatures compared to other grassland ecoregions (Ricketts et al. 1999). Smoky Valley Ranch is intersected by the Smoky Hill River (Figure 2), which is lined with mature cottonwood trees (*Populus sp.*). On SVR, the Smoky Hill River only flows during precipitation events but maintains year-round water in sporadic depressions. The river separates the property into two distinct ecological zones. Northeast of the river, the majority of SVR, is shortgrass prairie dominated by buffalograss (*Bouteloua dactyloides*) and blue grama (*Bouteloua gracilis*). The area is broken by chalk bluffs and some rolling hills. The area southwest of the river is primarily sand sage (*Artemisia filifolia*) prairie near the river, a reseeded plant community dominated by sideoats grama (*Bouteloua curtipendula*), and areas of chalk flats that are dominated by little bluestem (*Schizachyrium scoparium*) and other tallgrass species (Bain 2016).

The black-tailed prairie dog core area comprised approximately 1479 ha (~20% of the total area of the ranch; Figure 2), which exceeded the goal of ~600 ha prescribed in the management plan for SVR (Bain 2016). However, the habitat quality in the core area was significantly reduced by encroaching monocultures of purple three-awn. Smoky Valley Ranch is in the breeding range of the Burrowing Owl (Figure 1; Poulin et al.

2011), and The Nature Conservancy actively maintains prairie dog colonies. Therefore, the ranch was an ideal location for this study.

Visual Encounter Surveys

Visual surveys for Burrowing Owls were conducted from 21 April – 31 May 2018. Surveys were conducted from 0800 – 1200 and 1600 – 1800 within or near the prairie dog core area (Figure 2) to maximize the chance of visual encounters. During visual surveys, I drove an all-terrain vehicle around the edges of prairie dog colonies and used binoculars to survey for Burrowing Owls exhibiting defensive behavior. Burrowing Owls were also observed exhibiting behaviors such as preening or burrow maintenance, which helped identify occupied burrows (Desmond and Savidge 1996).

A burrow probe – Peeper™ Video Probe (Sandpiper Technologies, Inc.) – was used to obtain visual confirmation of an active nest (Figure 3). Burrows were considered occupied if there were eggs or adults present (Figure 4), nest materials present, or if there was obvious debris – shredded cattle dung, avian feces, sticks, etc. – at the entrance to the burrow (Figure 5; Desmond and Savidge 1996). The burrow location was recorded with a hand-held global positioning system (GPS; Figure1), and the burrow was given a unique identification code.

Unoccupied Burrow Selection

To determine if vegetative structure had a significant effect on nest selection in Burrowing Owls, I classified vegetation around both occupied and unoccupied burrows. Unoccupied burrows were located at least 50 m from the area captured by UAS flights for occupied burrows but located within 100 m of the nearest occupied burrow to provide a comparison of the habitats available to the owl.

Unoccupied burrows were selected by generating a list of paired random compass directions and random distances. When an occupied burrow was identified, the next direction-distance pair on the list was used to locate an unoccupied burrow. If no burrow was discovered, or in rare cases if there was another occupied burrow at that location, then the next direction-distance pair was used until an unoccupied burrow was located. The locations of unoccupied burrows were recorded with a GPS and were given labels similar to those for occupied burrows.

Daubenmire Vegetative Structure

Vegetation surrounding both occupied and unoccupied burrows was classified by using a modified Daubenmire classification scheme in which vegetative cover was estimated at different heights above the surface to capture variation in vertical structure (Sammon and Wilkins 2005). Four 20-m transects, one oriented to each cardinal direction and centered on the burrow opening, were established by placing wood stakes at 2 m, 5 m, 10 m, and 20 m from the burrow (Figure 6). These transects were established so data collection from both drone flights and Daubenmire protocols could be collected at nearly the same time to reduce temporal variability in comparisons.

Daubenmire classifications were conducted between 08 June 2018 and 12 June 2018. A 1-m x 1-m frame constructed from white PVC pipe was substituted for the traditional Daubenmire frame (20 cm x 50 cm) because the frames needed to be visible from above during UAS flights. The Daubenmire frame was further modified so vegetative cover could be quantified above the ground. Within each plot, vegetative cover was classified at ground level, 10 cm above the ground, and 20 cm above the ground. Vegetation was categorized as grass (noninvasive), bare ground, litter (standing dead and lying dead), purple three-awn, and forb. Each category was given a Daubenmire classification between 0 and 6 (0 = 0% cover, 1 = 1-5% cover, 2 = 6-25% cover, 3 = 26-50% cover, 4 = 51-75% cover, 5 = 76-95% cover, 6 = 96-100% cover). Before analysis, the Daubenmire classifications were converted to the midpoint percentage.

Vegetative cover for each burrow was averaged for each cover category so each cover category would have one value for each burrow. This was necessary to assess the data with a generalized linear model (GLM). For this GLM, the response variable was presence and absence (1 and 0, respectively) of Burrowing Owls. The predictor variables were the average cover (proportion) of each cover category at each height (0, 10, and 20 cm). Before performing the GLM, I used a principal component analysis as an exploratory tool to identify the variables that would make the greatest contributions to the predictive model (Canoco 5.10). None of the predictor variables were normally distributed. Specifically, all predictor variables were right skewed. Therefore, all predictor variables were transformed with a logarithm transform before analysis.

All other statistical analyses were conducted in the R statistical software (version 3.3.2), and the significance level for all statistical tests was $\alpha = 0.10$ to remain consistent with MacCracken et al. (1985). Before generating a GLM, the predictor variables were assessed for collinearity. Predictors were considered collinear if they had a correlation coefficient greater than or equal to 0.80. If two or more predictors were collinear, the predictor with the largest correlation coefficient with the response variable was retained, and the other variable(s) were removed. The first GLM indicated bare ground and forb cover were significant predictors. Therefore, a second GLM was generated, which included only bare ground and forb cover. This reduced model was assessed for outliers, linearity, and normality (le Cessie-van Houwelingen) and was not significantly different from the full model, and therefore preferred.

Finally, the model was cross-validated with a bootstrapping technique (R package boot). This cross-validation is an iterative process in which the data were divided into six approximately equal parts, and a model was generated six times. In each iteration, one of the six parts of the data (test sample) was not included, while the other data (training sample) were used to generate the model. The predicted occurrence (from the model) was compared to the known occurrence of the test sample. The result of the bootstrapping procedure was a percentage of how often the models failed to predict the presence and absence of owls.

Aerial Imagery

The UAS used to collect aerial imagery was a DJI Phantom 4 Pro (Shenzhen Dajiang Baiwang Technology Co., Ltd.) equipped with a 20-megapixel sensor (Figure 7, Appendix 1). Flights were conducted between 0900 – 1500 on 08 June, 09 June, and 12 June 2018. The Pix4D Capture mobile application was used to automate each flight (Appendix 1). The four transects around each burrow resulted in a 40-m x 40-m square (Figure 8). To ensure sufficient data density at the edges of the sample area, each automated flight captured an area 50 m x 50 m. Flight altitude was 30 m above ground level (AGL), and image overlap was 80%. The average relative spatial resolution in each image was 0.0083 m/pixel (Appendix 1, Table 1), approximately 120 times finer than imagery obtained from commercially available satellites (1 m/pixel). During UAS flights, frames were placed in 20-m transects, in the same locations as during the Daubenmire data collection, to provide reference points in the aerial imagery (Figure 6).

Photogrammetric Surface Structure

Aerial imagery was processed in the Pix4D Mapper (version 4.3.31). The UAS collected an average of 110 images per burrow, and the software stitched the images together to generate a single, georeferenced mosaic of the area. During this process, tie points (points that are shared among many images) were generated and placed in three-dimensional space by including their latitude, longitude, and elevation as assigned by the GPS onboard the UAS (Appendix 2). After tie points were generated, the processing area for the plot was specified. The processing area was drawn such that any extraneous tie points outside the core 40-m x 40-m plot were removed to reduce the time it took to generate three-dimensional products and to improve the quality of those products.

The tie points within the processing area for each burrow were used to generate a georeferenced densified point cloud. A minimum of six tie points matching between two images were required for those images to be included in the densification (Appendix 2). Even with these strict parameters, the mean point cloud density was still high (x = 25672 points/m^3; Table 1). Subsequently, a three-dimensional textured triangle mesh was generated from the tie points (Appendix 2); however, these meshes were not georeferenced so they were only used for visual assessment of the plots. The final product from the aerial imagery was a two-dimensional, georeferenced orthomosaic (a high-resolution image of the entire burrow plot; Figure 6).

Visual Obstruction

The aerial imagery and densified point cloud generated from it provided a quantitative framework to assess differences between occupied and unoccupied burrows. Specifically, I attempted to quantify visual obstruction across the area around each burrow. Visual obstruction was estimated from a lidar point cloud (LAS) dataset derived from the densified point cloud (Appendix 2) in ESRI ArcMap (version 10.5). The LAS dataset was used to generate a triangulated irregular network (TIN) to represent the surface (vegetative) structure (Figure 8). Within the TIN, triangle vertices that are closer together indicate greater variation in elevation, and vertices that are further apart reflect less variation in elevation.

I designated observer and target points within the TIN surface. The observer point was placed at the burrow opening and was offset 0.25 m above the surface to represent a Burrowing Owl looking out from the burrow. Twenty target points were placed on the surface 20 m from the burrow in a circular pattern (Figure 8). Lines of sight were applied between the observer point and each target point. Along the lines of sight, sections were coded as 1 if the “observer” would be able to see the target point at that location and 0 if they would not due to obstruction by the TIN surface (Figure 9). The total obstruction (in meters) on each line was calculated.

To determine if there were differences in visual obstruction between occupied and unoccupied burrows, I used chi-square goodness of fit tests. The obstructed distance along each transect (n =20) at each burrow was converted to the number of obstructed pixels by dividing the obstructed distance (m) by the resolution (m/pixel) of the TIN surface (Table 1). Obstructed pixel counts at unoccupied burrows were used as the expected values. These expected values were used to calculate the expected percentage of obstruction at a burrow. If there were no difference between occupied and unoccupied burrows, the obstruction at occupied burrows would be the same as the expected value quantified from unoccupied burrows. Chi-square goodness of fit tests were used to compare the total obstructed pixels, the obstructed pixels 0-2 m from the burrow, the obstructed pixels 2-5 m from the burrow, the obstructed pixels 5-10 m from the burrow, and the obstructed pixels 10-20 m from the burrow to determine if there were any regions that were particularly important for burrow selection.

RESULTS

Burrowing Owl Nests

During visual encounter surveys, owls were observed on 21 occasions. From these 21 visual encounters, I identified 15 occupied burrows. Most occupied burrows were discovered outside the prairie dog core area and relatively close to water sources (Figure 2). One occupied burrow (BOO14) might have been depredated. There was evidence of nesting when the burrow was initially discovered, but during the vegetation survey on 09 Jun 2018, I observed blood at the entrance to the burrow and adult owls were not observed near the burrow again. The focus of my study was not on the natural history or nesting success of the owls so no data from adults, eggs, or nestlings were collected.

Daubenmire Vegetative Structure

The PCA indicated there were four distinct groups of burrows based on Daubenmire vegetative structure (Figure 10). One group was supported by high values for bare ground and low values for forb cover, and five of seven burrows in that group were occupied. The next group was supported by high values for litter at all three heights and forb cover at 10 cm and 20 cm, and five of seven burrows in that group were unoccupied. The third group was supported by high values for grass cover at all three heights, and five of eight burrows in that group were unoccupied. The final group was supported by low values for purple three-awn cover, and there was no clear separation of occupied and unoccupied burrows in that group.

After removing collinear predictors, the first generalized linear model of Daubenmire vegetative structure included bare ground, forb cover, litter cover, purple three-awn cover, grass cover 10 cm above the ground, and litter cover 10 cm above the ground as predictors. Only bare ground and forb cover were significant ($Z = 2.29$, $df = 23$, $p = 0.022$ and $Z = -2.54$, $df = 23$, $p = 0.011$, respectively). Presence of Burrowing Owl increased with increased bare ground, and presence decreased with increased forb cover. Therefore, a reduced model that only included bare ground and forb cover was generated.

In the reduced model, both bare ground and forb cover remained significant ($Z = 2.47$, $df = 27$, $p = 0.014$ and $Z = -2.48$, $df = 27$, $p = 0.013$, respectively). The reduced model was compatible with all diagnostic tests. The null expectation would be for the model to incorrectly identify burrows 50% of the time. The reduced model here incorrectly predicted the presence and absence of Burrowing Owls 13% of the time. This model suggested that the presence of Burrowing Owl increased with bare ground cover (Figure 11) and decreased with forb cover (Figure 12).

Visual Obstruction

Unoccupied burrows had significantly more obstruction than occupied burrows ($X^2 = 266$, df = 9, $p < 0.001$; Figure 13). Unoccupied burrows had significantly more obstruction than occupied burrows in the 0-2 m range ($X^2 = 54.0$, df = 9, $p < 0.001$; Figure 14). In the 2-5 m range, unoccupied burrows were more obstructed than occupied burrows ($X^2 = 179$, df = 9, $p < 0.001$; Figure 15). Unoccupied burrows had significantly more obstruction than occupied burrow in the 5-10 m range ($X^2 = 334$, df = 9, $p < 0.001$; Figure 16). Finally, in the 10-20 m range, unoccupied burrows had significantly more obstruction than occupied burrows ($X^2 = 198$, df = 9, $p < 0.001$; Figure 17).

DISCUSSION

Unmanned aerial systems have been successfully implemented to significantly reduce the required time and cost of many processes formerly completed by on-the-ground technicians or manned aircraft. These include, but are not limited to, counts of large organisms, monitoring the health and structure of crops, and classifying trees. In my study, imagery collected by UAS was used to generate three-dimensional models of surface structure. Similar models have been used to quantify the structure of crops and other vegetation (Grenzdörffer 2014). However, fine-scale models of shortgrass ecosystems had not previously been generated by using UAS imagery. Models of surface structure were used here to quantify visual obstruction, replacing data that previously would have been collected with a time-consuming protocol such as the Robel method (Robel et al. 1970).

The results of my study suggest that Burrowing Owls selected burrows that were surrounded by little vegetation. Any vegetation that did occur at occupied burrows was sparse and low to the ground. Estimates of Daubenmire vegetative structure suggest that Burrowing Owls selected burrows surrounded by high proportions of bare ground. However, the relationship between bare ground and presence was relatively weak (Figure 11) compared to the relationship observed between presence and visual obstruction (Figure 13). The area around occupied burrows had low obstruction and this might be based on the ability of Burrowing Owls to see threats approaching the burrow from a distance. Therefore, visual obstruction might be a more direct measure of selection than the total vegetation cover or the total cover of specific functional groups.

Traditional vegetation quantification techniques are prone to temporal bias, due to the amount of time they take to complete across large areas. Daubenmire vegetative structure data collection took approximately eight hours over several days and would have taken significantly longer had more burrows been occupied. This time does not include the several weeks it took to establish transects at each burrow. Data collection flights with the UAS, on the other hand, were all completed within five days, essentially eliminating any temporal bias. Each data flight (n = 30) took approximately seven minutes. Preparing the plots for flight took approximately 15 minutes each, but this preparation (placing Daubenmire frames as previously described) was only necessary to provide reference points for comparison to traditional methods. Therefore, without that preparation, data flights could have all been completed in a matter of hours. With the successful use of UAS to generate models of vegetative structure, on-the-ground data collection and the overall time for data collection could be significantly reduced.

Grasslands and the species that depend on them have declined severely since European colonization primarily due to conversion to cropland. Other anthropogenic changes, including climate change, have allowed previously diverse plant communities to become increasingly overtaken by one or a few species. Purple three-awn is one such species, and it has become a monoculture in many parts of Smoky Valley Ranch. The Nature Conservancy has struggled to find an effective management plan to slow or stop the spread of purple three-awn and other invasive plant species.

The encroachment of purple three-awn at SVR has reduced prairie dog density and forage quality for cattle and bison. For birds, however, particular plant species often do not affect species diversity (MacArthur and MacArthur 1961) or habitat selection choices (Delise and Savidge 1997). The presence of purple three-awn appeared not to affect nest selection in analyses of vegetative structure based on the Daubenmire classifications. However, plant species were not identified in the models of surface structure generated by photogrammetry from UAS imagery. Therefore, purple three-awn could have been one of many plants that contributed to visual obstruction. A focus of future research should be to collect UAS imagery wherein plants could be identified to determine if Burrowing Owls make selection choices based on the visual obstruction of specific plants.

Purple three-awn did not negatively affect selection in my study. However, continued expansion of purple three-awn will further reduce black-tailed prairie dog abundance and the forage quality for grazers. Eventually, this will negatively affect Burrowing Owls because reduced grazing will result in increased vegetative structure and increased visual obstruction. Therefore, purple three-awn management should continue so Burrowing Owls continue to have nesting habitat in one of the few remaining areas of native prairie in their breeding range.

Because visual obstruction best predicted the presence of Burrowing Owls, visual obstruction should be the focus of future studies focused on nest-burrow selection in Burrowing Owl. However, data collection by traditional techniques such as the Robel method is time-consuming and labor-intensive. Therefore, other methods, such as photogrammetry with UAS imagery, should be explored further. My study was conducted in a shortgrass prairie ecosystem, which had relatively sparse and short vegetation. Even in this environment, UAS imagery provided resolutions that were sufficient to generate models that predicted nest-burrow selection based on visual obstruction. Accordingly, these techniques would likely be applicable in other ecoregions and for investigating the selection choices of other organisms.

Grassland nesting birds are the most seriously threatened group of birds in North America due to the conversion of grassland to cropland. Encroachment by woody plant species due to fire suppression also negatively affects these birds (Hunter 1990, Lymn and Temple 1991). Grassland ecosystems are highly variable due to grazing, inconsistent precipitation, and fire (Winter et al. 2005). As a result, birds that nest in these systems experience spatial and temporal variation in abundance (Igl and Johnson 1997) and success (George et al. 1992). Due to this variation in grassland habitat and the resulting fluctuations in grassland bird abundance and nesting success, consistent and extensive fieldwork must be completed to monitor populations and their habitat. Most of this fieldwork involves on-the-ground quantification of vegetative structure and visual obstruction. Incorporating UAS generated imagery might substantially reduce required fieldwork if three-dimensional surface models are adequate predictors of selection choices made by birds that nest in grasslands.

The potential uses of UAS for wildlife monitoring extend beyond grassland ecosystems and extend beyond avian abundance, selection, and success. Models of vegetative structure could be used to quantify available forage for grazing mammals or to quantify escape-cover from predators for many species, not just birds. Forest ecosystems are less variable than grasslands and require less frequent monitoring, but UAS could be used to quantify vegetative structure and visual obstruction for forest-dwelling organisms and reduce the cost of fieldwork.

Imagery collected by UAS also might be used in an integrative process with imagery collected at other scales, similar to how satellite imagery of different resolutions is used to quantify vegetative indices (Houborg et al. 2015). Commercial satellite imagery is expensive and often impeded by cloud cover, but it allows the analysis of larger areas than UAS. For investigations that include large extents, satellite imagery could be used to provide a general understanding of how the area changes over a long time, and UAS might be used to monitor the area more frequently and provide high temporal resolution in areas of concern.

However, with the successful application of UAS imagery to determine the effect of vegetative structure on Burrowing Owl nest-burrow selection in this study, The Nature Conservancy and Smoky Valley Ranch should have a much more efficient and data-rich vegetation monitoring program in which they will be able to use UAS imagery to determine areas in need of significant intervention to improve the quality of habitat available to all species.

Similar UAS monitoring programs could be implemented at federal wildlife refuges, state wildlife areas, and national parks to significantly reduce the amount of time and money it takes to monitor threatened plant and wildlife species. As the time a UAS can remain in flight increases, as the quality of sensors improves, and as the power of modeling software increases, the value of UAS for the fields of wildlife conservation and management will continue to increase.

The potential benefit of more efficient and accurate data collection with UAS has already begun to replace field collection methods and will continue to do so in the future. To fully maximize the potential of UAS, wildlife managers should be trained in UAS-based data collection techniques. In this way, people that work on the land every day and have an innate understanding of the system can contribute to the quality of data collected and form management plans that will provide the most benefit to as many of the species that have been negatively affected by human-induced change as possible.

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Table 1. Plot Size, Point Density, and Resolution for All Burrows.
The plot size for the UAS flight at each burrow (both occupied and occupied) along with the number of three-dimensional densified points per cubic meter and the final resolution of the georeferenced orthomosaic generated by Pix4D Mapper. The resolution (m/pixel) was used to convert the total obstructed distance at each burrow to total number of obstructed pixels in the visual obstruction analyses.

Burrow	*Plot Size (ha)*	*3D Densified Points/m^3*	*Resolution (m/pixel)*
BOO1	0.8382	27122.9	0.0083
BOU1	0.7658	32092.1	0.0077
BOO2	0.8574	24392.0	0.0085
BOU2	0.8425	25323.8	0.0084
BOO3	0.7997	24441.5	0.0083
BOU3	0.7666	28816.4	0.0079
BOO4	1.0959	25527.1	0.0088
BOU4	1.1111	21178.7	0.0093
BOO5	0.8175	24502.6	0.0084
BOU5	0.8271	22092.3	0.0084
BOO6	0.8372	25029.6	0.0085
BOU6	0.8656	23039.4	0.0088
BOO7	0.8561	20497.2	0.0088
BOU7	0.8099	22239.4	0.0082
BOO8	0.8322	27167.7	0.0082
BOU8	0.7622	31365.4	0.0077
BOO9	0.7899	27126.0	0.0080
BOU9	0.7796	27037.7	0.0079
BOO10	0.7840	22672.0	0.0082
BOU10	0.7316	25192.7	0.0075
BOO11	0.8318	23419.9	0.0086
BOU11	0.7912	26495.6	0.0082
BOO12	0.8036	28345.4	0.0080
BOU12	0.8011	24697.4	0.0081
BOO13	0.7490	28230.2	0.0078
BOU13	0.7482	31507.9	0.0077
BOO14	0.7881	28746.7	0.0079
BOU14	0.7826	27858.2	0.0078
BOO15	0.9426	20566.6	0.0091
BOU15	0.8559	23427.8	0.0086
Mean	0.8288	25671.7	0.0083

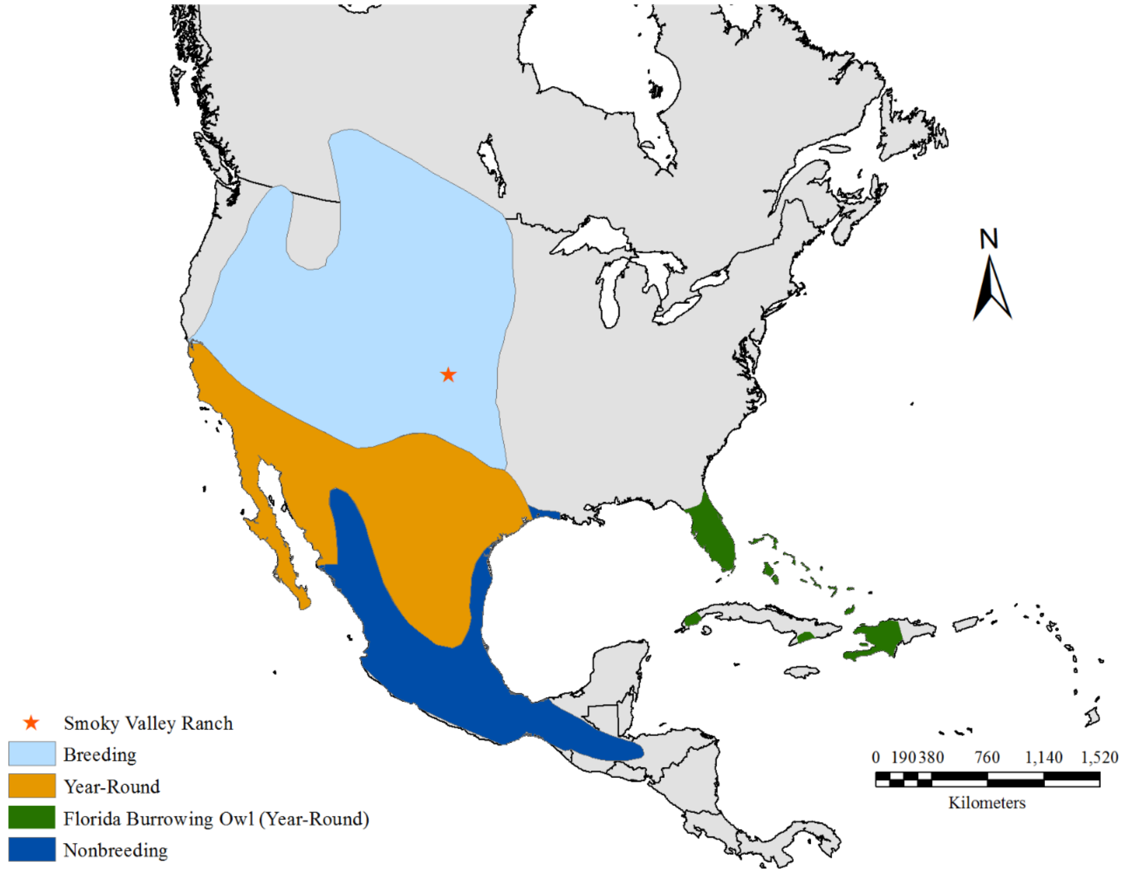


Figure 1. Burrowing Owl Species Range.
The species range of the Burrowing Owl (*Athene cunicularia*), indicating breeding, nonbreeding, and year-round ranges. Smoky Valley Ranch (red star) is within the breeding range of the Burrowing Owl. The range of the Florida Burrowing Owl subspecies (*A. c. floridana*) is also shown (modified from Poulin et al. 2011).

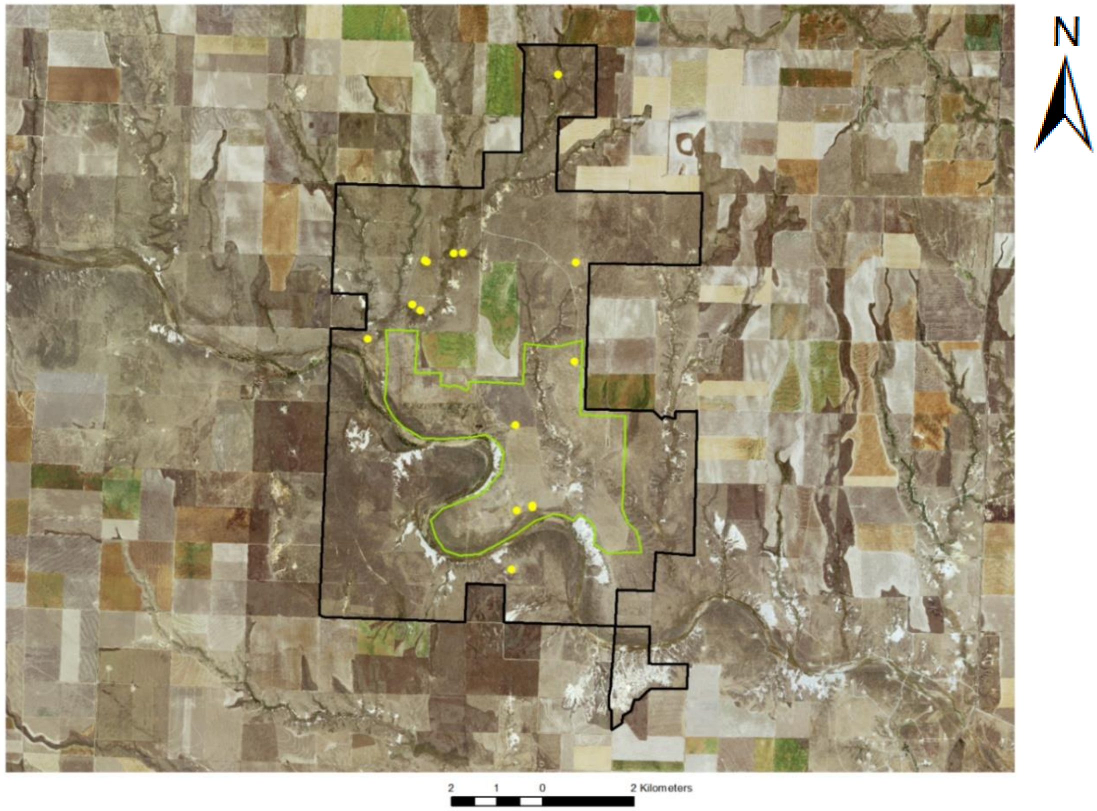


Figure 2. Smoky Valley Ranch and Burrowing Owl Nest Locations.
The borders of Smoky Valley Ranch are indicated in black, and the green border within the ranch delimits the area occupied by black-tailed prairie dogs (*Cynomys ludovicianas*). The Smoky Hill River intersects the ranch and separates the ranch into two distinct ecological zones. The locations of the 15 burrows occupied by Western Burrowing Owls are shown as yellow dots. These burrows were identified during visual encounter surveys between 21 April and 31 May 2018.

Figure 3. Peeper^{TM} Video Probe.
The Peeper^{TM} Video Probe (Sandpiper Technologies, Inc.) used to obtain visual confirmation of the presence of eggs, adult owls, or nest materials in burrows.

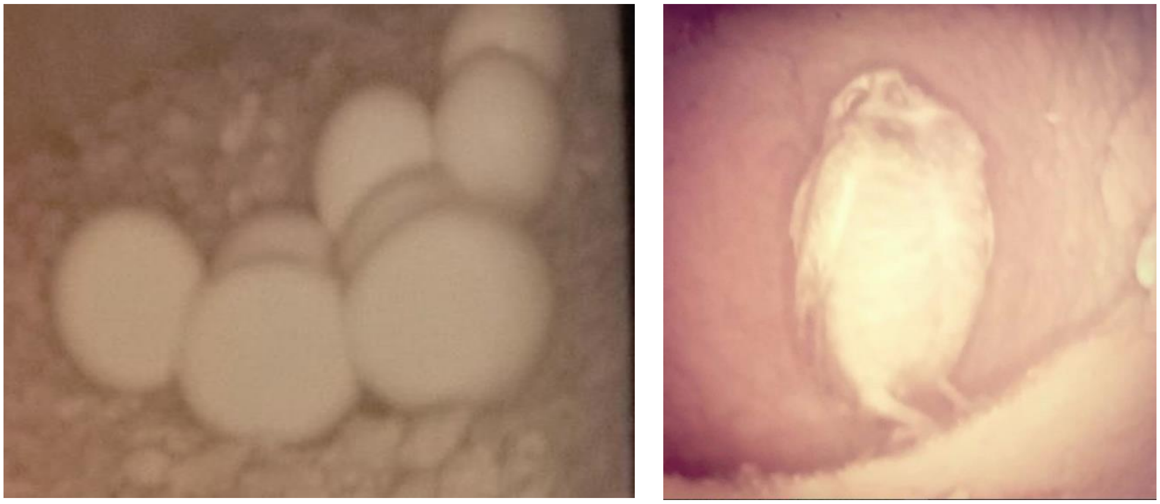


Figure 4. Eggs and Adult Owl Inside a Burrow.
Burrowing Owl eggs in burrow BOO7 and an adult Burrowing Owl in burrow BOO15. These images were captured with the Peeper[TM] Video Probe (Sandpiper Technologies, Inc.). The presence of eggs and adult owls in the burrow were two of the methods by which burrows were designated as occupied.

Figure 5. Entrance to Occupied Burrow.
The entrance to burrow BOO11. This burrow had regurgitated pellets, shredded cattle manure, and other debris surrounding the entrance. There was often shredded cattle manure lining the tunnel down into the burrow.

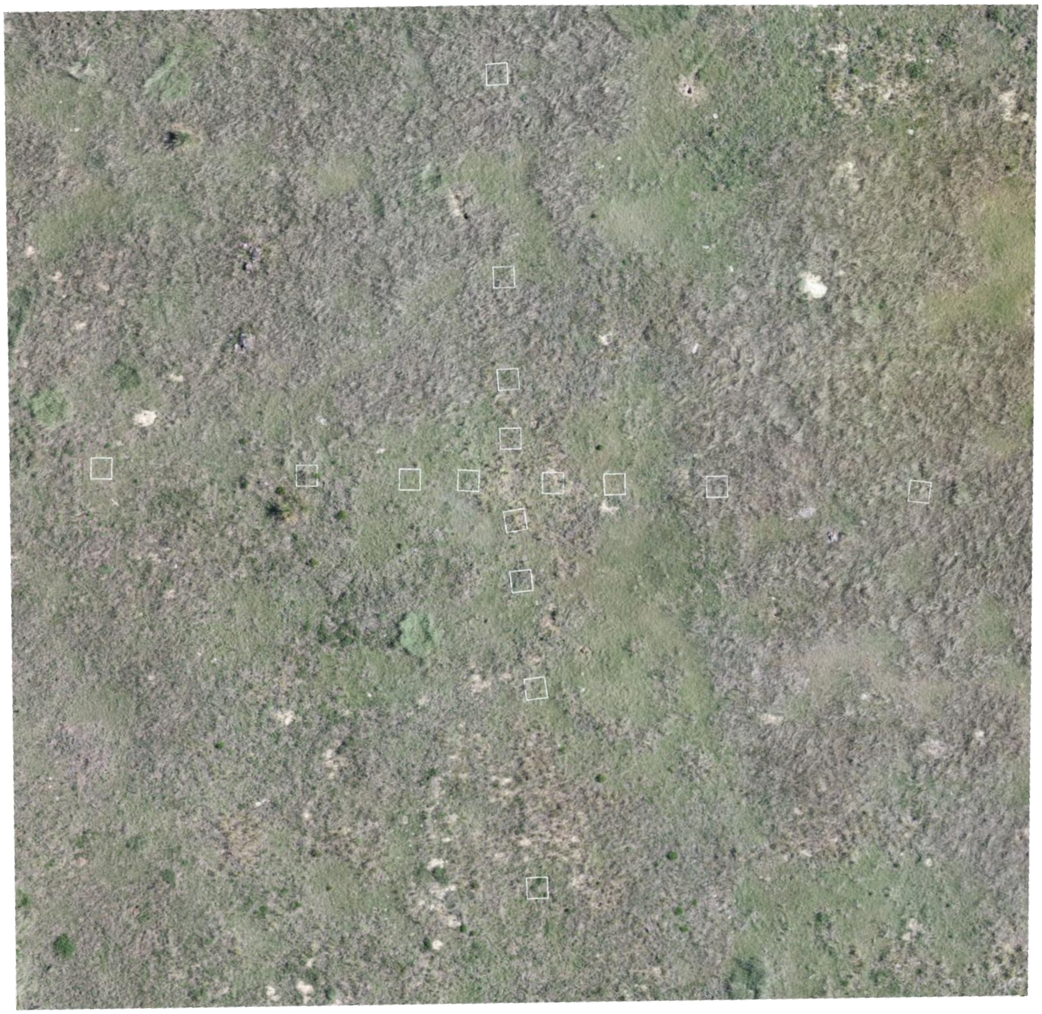


Figure 6. Georeferenced Orthomosaic of Unoccupied Burrow.
Aerial image collected with the Phantom 4 Pro unmanned aerial system. The 1-m x 1-m frames were deployed in four 20-m transects at each cardinal direction around the burrow. Daubenmire vegetative structure was quantified along each transect at intervals of 2 m, 5 m, 10 m, and 20 m.

Figure 7. DJI Phantom 4 Drone.
The unmanned aerial system used to collect aerial imagery of occupied and unoccupied burrows at Smoky Valley Ranch: DJI Phantom 4 Pro drone equipped with a 20-megapixel Red-Green-Blue sensor. Detailed specifications are in Table 1.

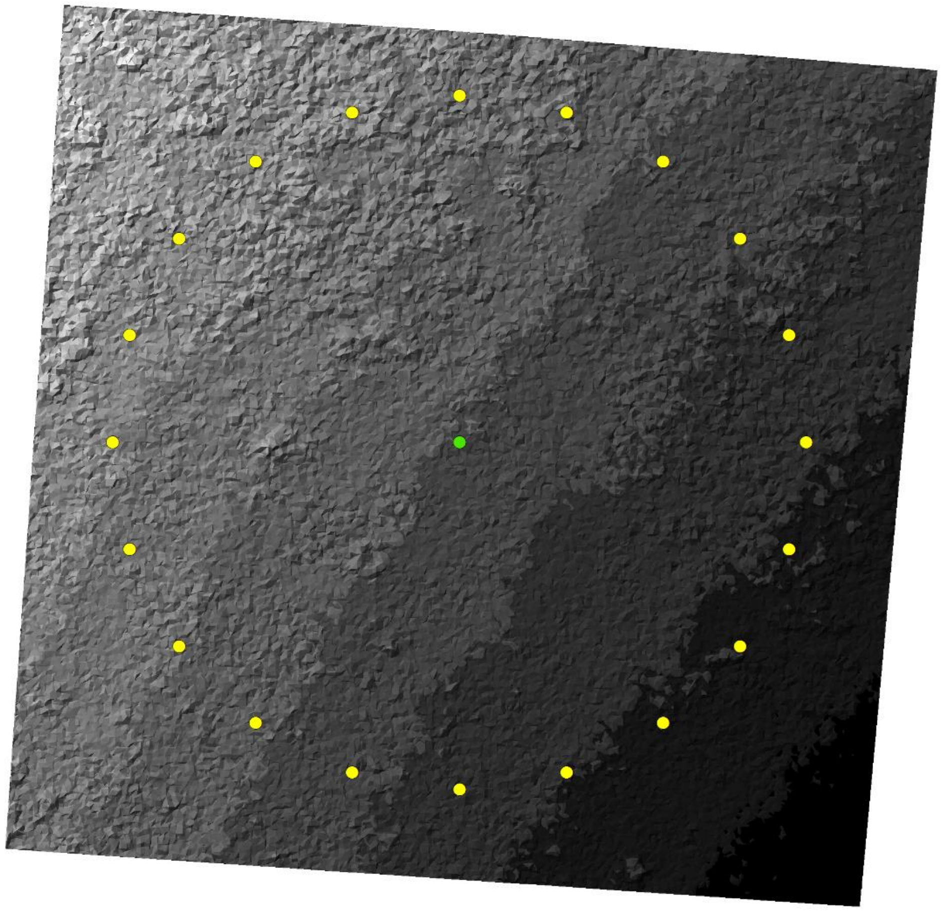


Figure 8. Triangulated Mesh with Visual Obstruction Points.
Triangulated irregular networks (TINs) were generated for each burrow. Triangle vertices are closer together where there is more variation in elevation and further apart where there is less variation in elevation. Darker (black) areas are at lower elevation than lighter (white) areas. The TIN shown here was generated for unoccupied burrow BOU10. To quantify visual obstruction caused by surface features, an observer point (green) and target points (yellow) were placed on the surface. The observer point was offset above the surface 0.25 m to simulate a Burrowing Owl (*Athene cunicularia*) looking out from the burrow entrance.

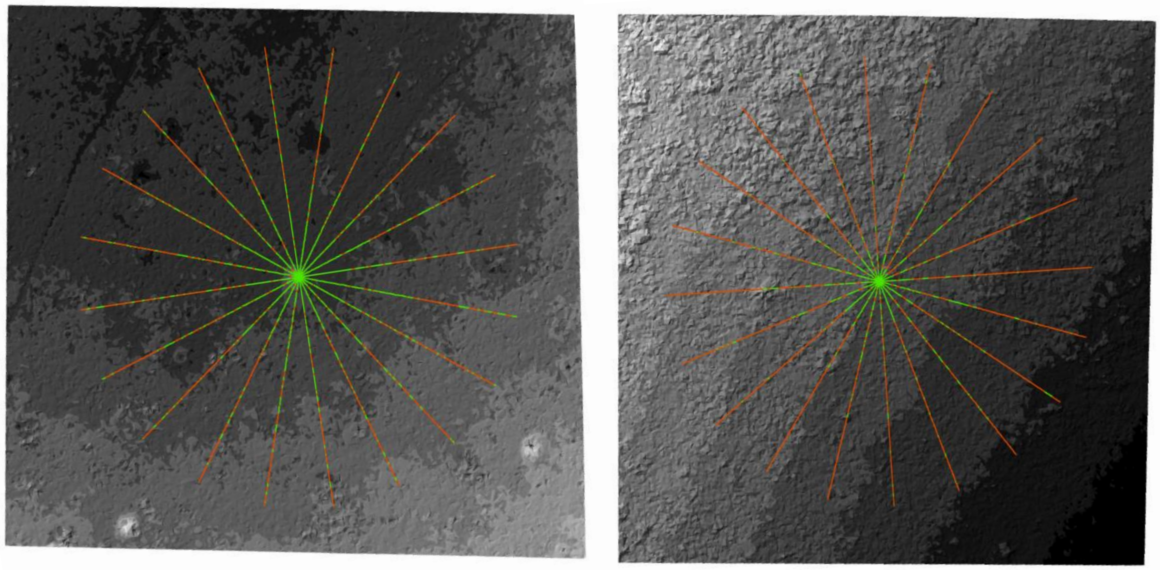


Figure 9. Visual Obstruction Lines.
Lines of sight for an occupied burrow (left, BOO3) and an unoccupied burrow (right, BOU10). Unoccupied burrows had significantly more obstruction along sight lines (shown in red) than occupied burrows.

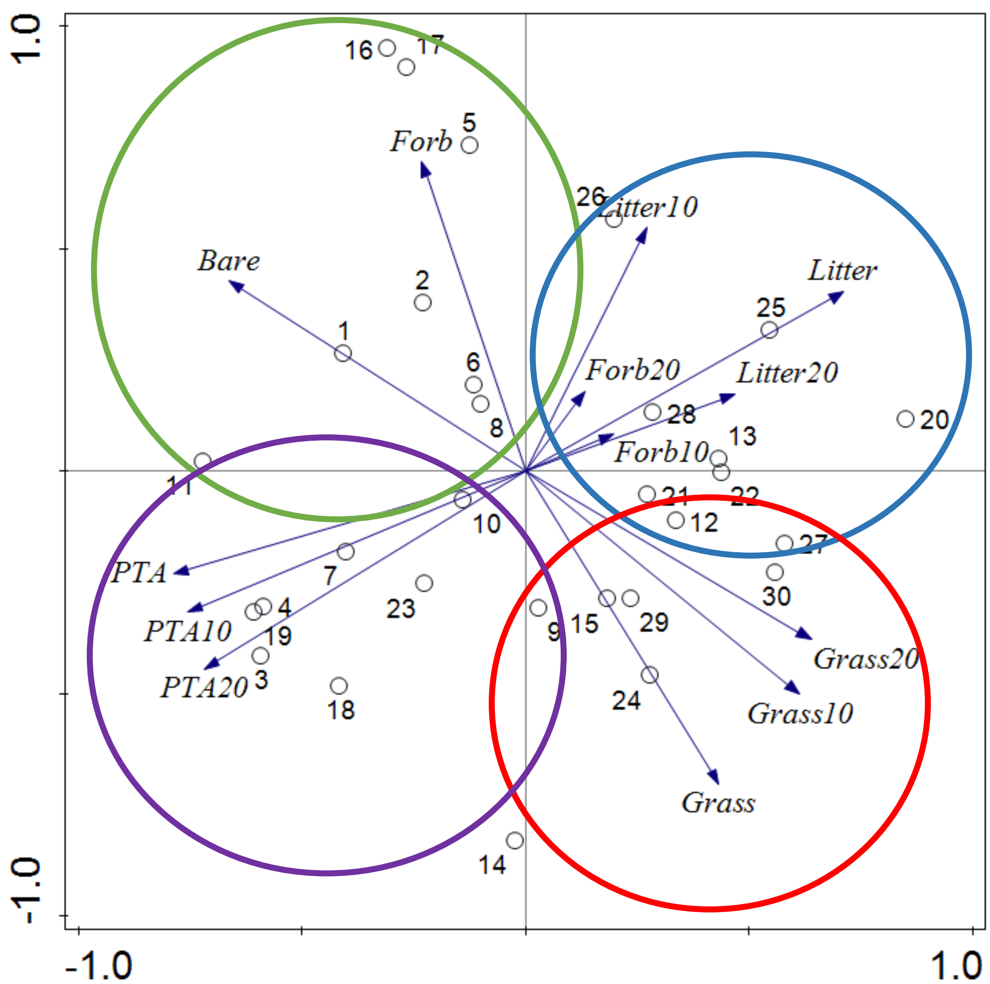


Figure 10. Principal Component Analysis with Daubenmire Structure Data. The principal component analysis of Daubenmire vegetative cover classes. Four groups of burrows are indicated by the colored circles. The numbers represent burrows (1-15 are occupied burrows and 16-30 are unoccupied burrows). The predictor variables (the logarithm transform of Daubenmire vegetative cover classes) are shown at the end of arrows, and the length of the arrow indicates the relative influence the variable had on the location of the burrows in the ordination space.

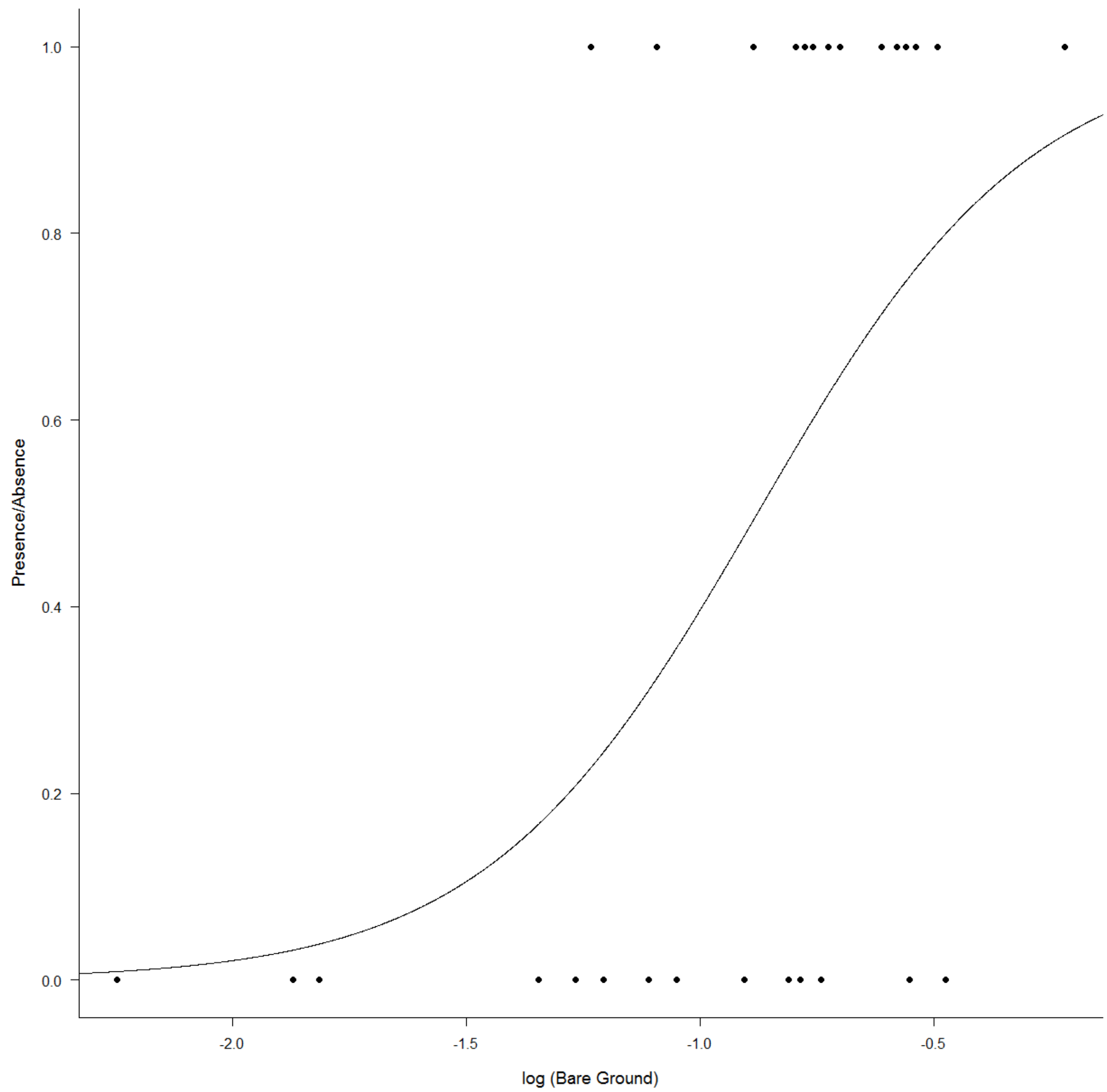


Figure 11. Generalized Linear Model of Bare Ground and Presence.
The generalized linear model for bare ground and its effect on presence and absence of Burrowing Owls. Presence of Burrowing Owls increased as bare ground cover increased ($Z = 2.47$, $df = 27$, $p = 0.014$).

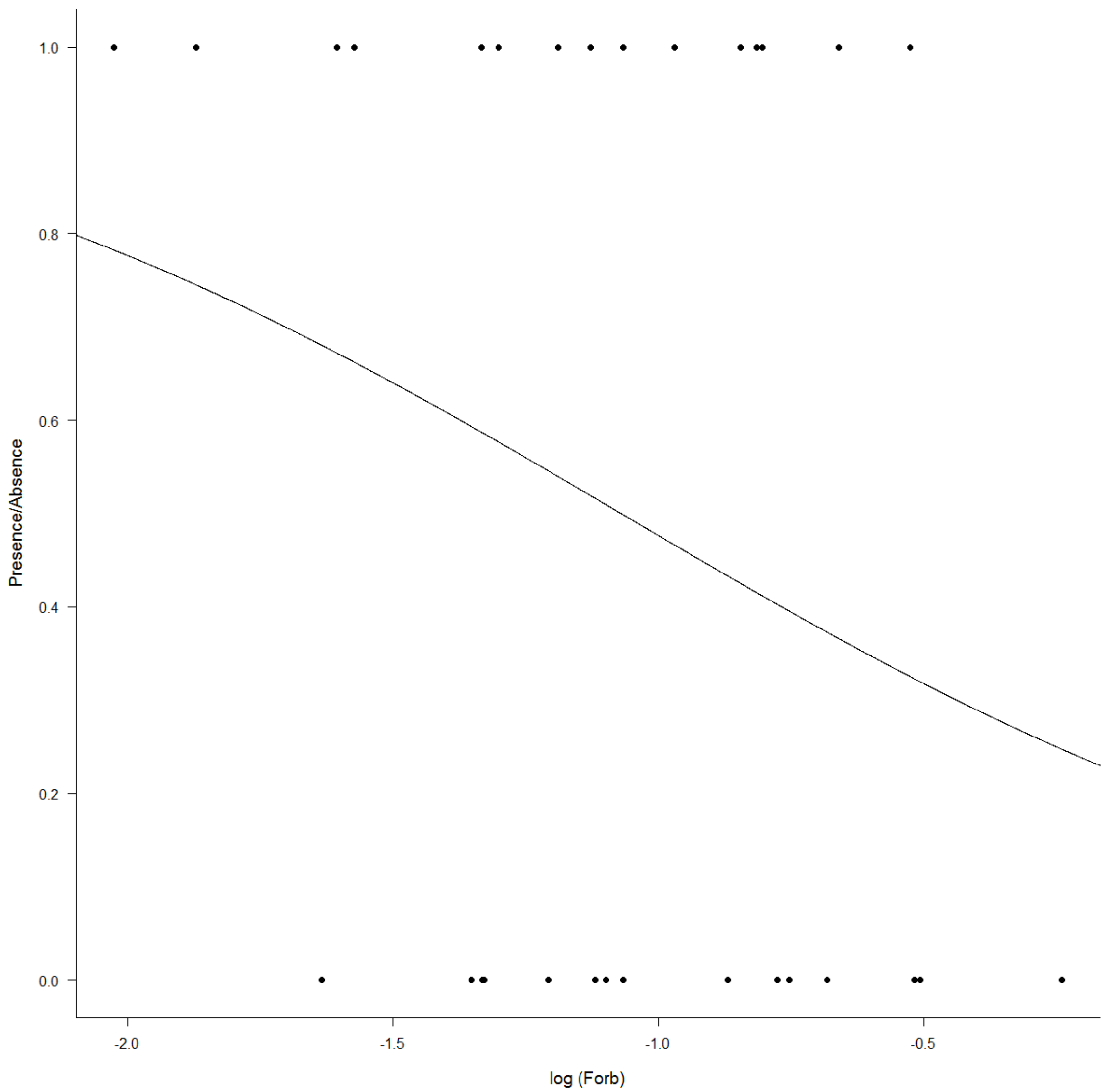


Figure 12. Generalized Linear Model of Forb and Presence.
The generalized linear model for forb cover and its effect on presence and absence of Burrowing Owls. Presence Burrowing Owls decreased as forb cover increased (Z = -2.48, df = 27, p = 0.013).

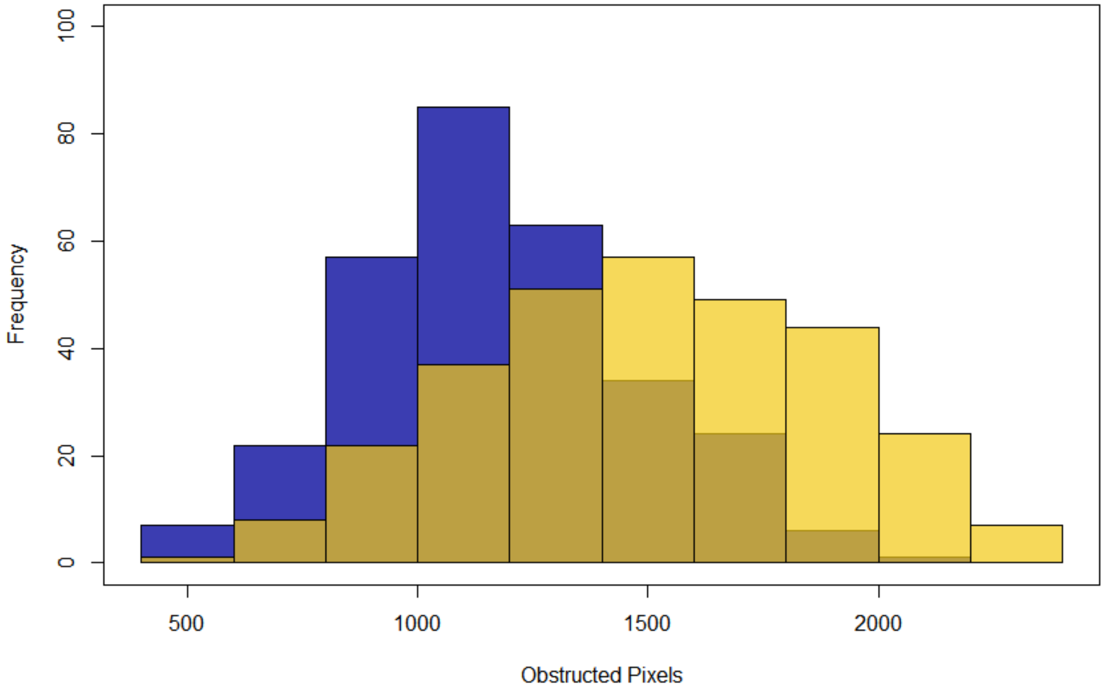


Figure 13. Distribution of Total Obstruction at All Burrows.
The distribution of total number of obstructed pixels at occupied burrows (blue) overlapped by the distribution at unoccupied burrows (yellow). The total number of obstructed pixels at unoccupied burrows was significantly greater than at occupied burrows ($X^2 = 266$, df = 9, $p < 0.001$).

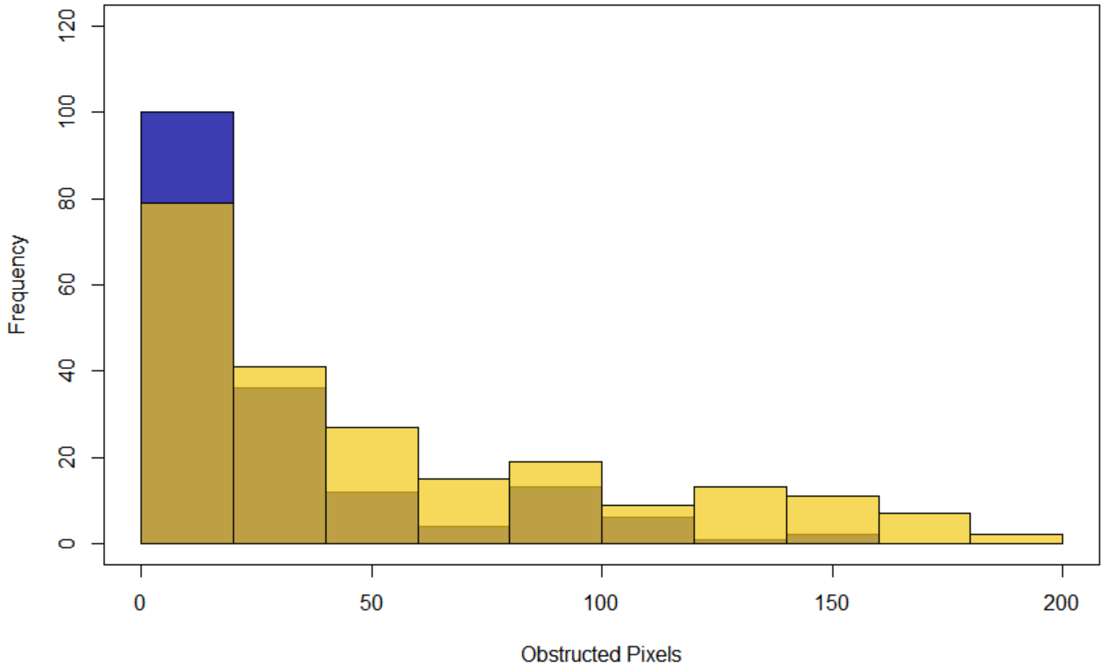


Figure 14. Distribution of Obstruction 0-2 m from All Burrows.
The distribution of obstructed pixels 0-2 m from the burrow at occupied burrows (blue) overlapped by the distribution at unoccupied burrows (yellow). The number of obstructed pixels 0-2 m from the burrow at unoccupied burrows was significantly greater than at occupied burrows ($X^2 = 54.0$, df = 9, $p < 0.001$).

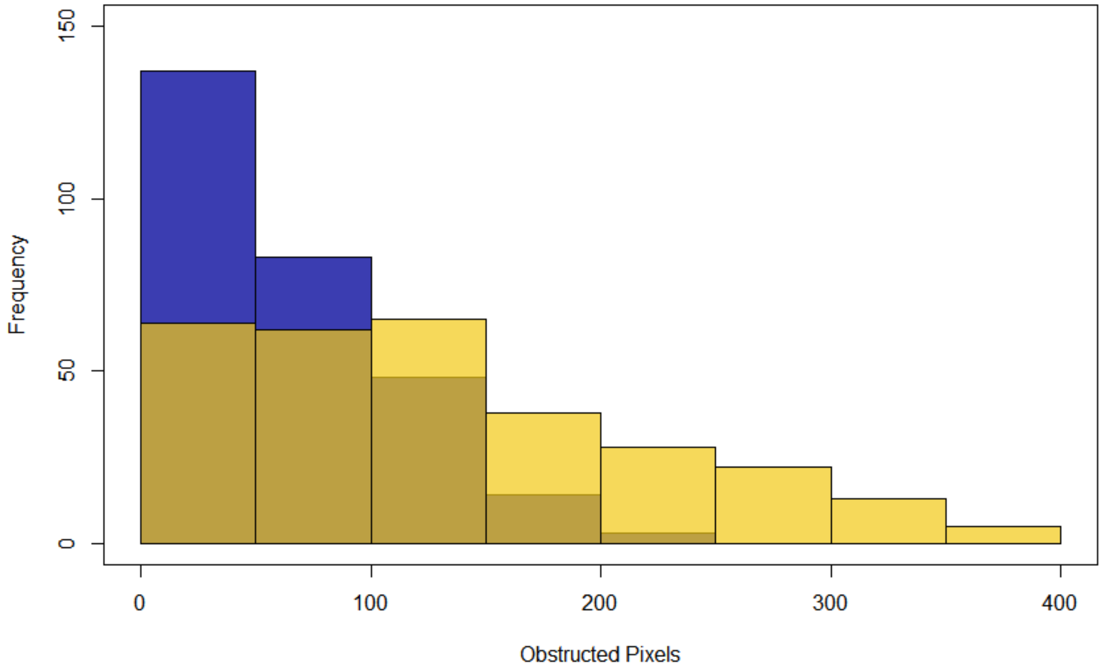


Figure 15. Distribution of Obstruction 2-5 m from All Burrows.
The distribution of obstructed pixels 2-5 m from the burrow at occupied burrows (blue) overlapped by the distribution at unoccupied burrows (yellow). The number of obstructed pixels 2-5 m from the burrow at unoccupied burrows was significantly greater than at occupied burrows ($X^2 = 179$, df = 9, $p < 0.001$).

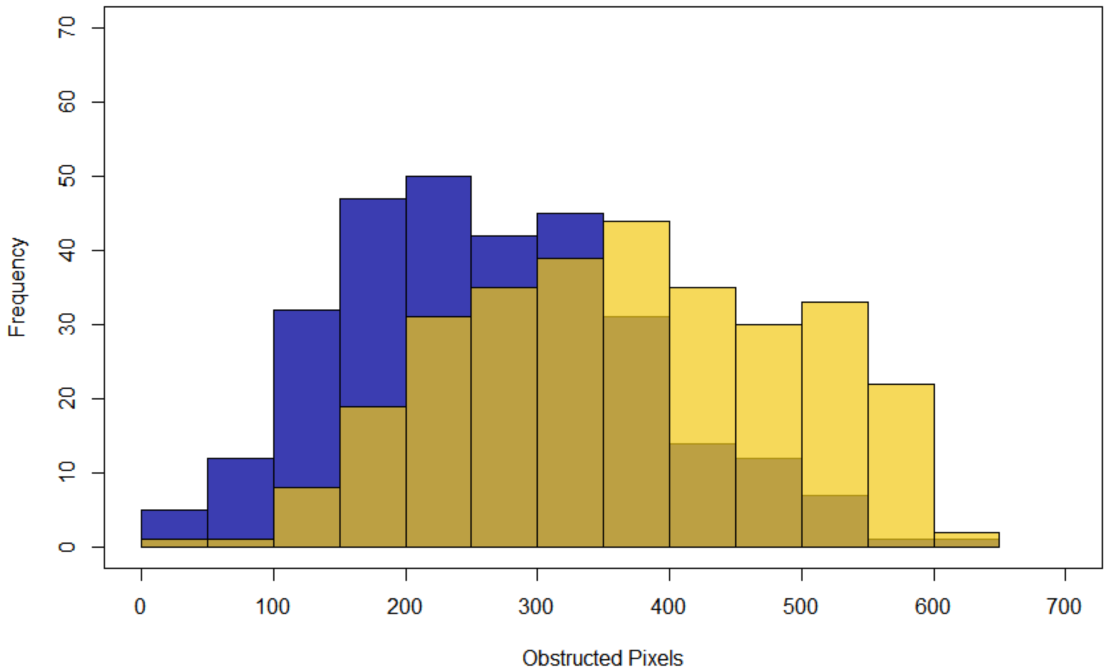


Figure 16. Distribution of Obstruction 5-10 m from All Burrows.
The distribution of obstructed pixels 5-10 m from the burrow at occupied burrows (blue) overlapped by the distribution at unoccupied burrows (yellow). The number of obstructed pixels 5-10 m from the burrow at unoccupied burrows was significantly greater than at occupied burrows ($X^2 = 334$, df = 9, $p < 0.001$).

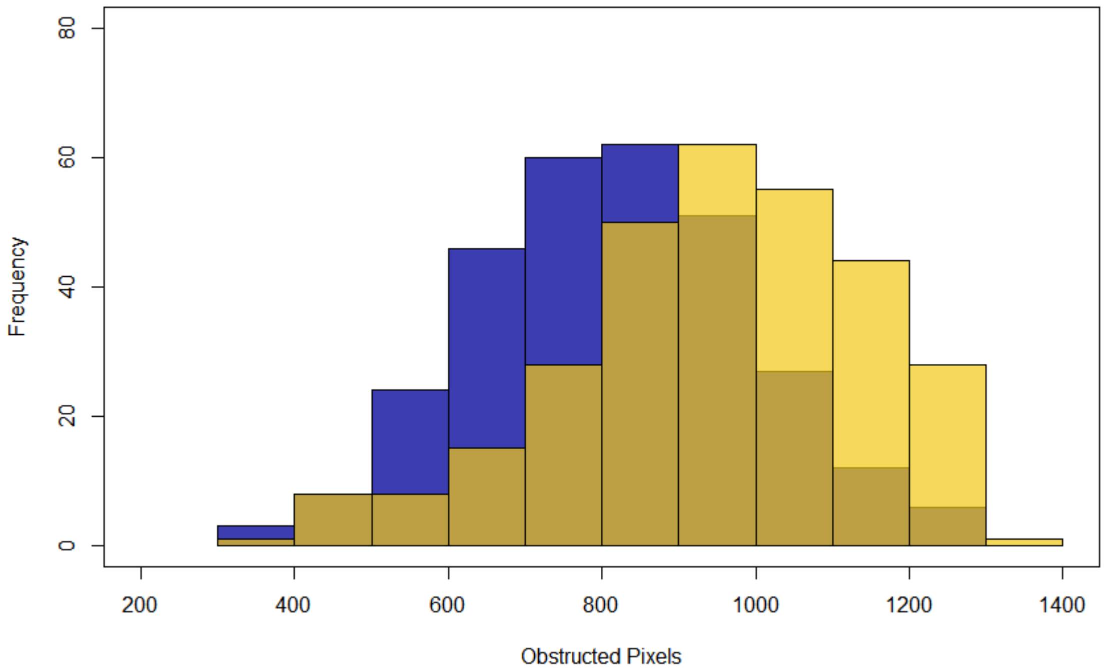


Figure 17. Distribution of Obstruction 10-20 m from All Burrows.
The distribution of obstructed pixels 10-20 m from the burrow at occupied burrows (blue) overlapped by the distribution at unoccupied burrows (yellow). The number of obstructed pixels 10-20 m from the burrow at unoccupied burrows was significantly greater than at occupied burrows ($X^2 = 198$, df = 9, $p < 0.001$).

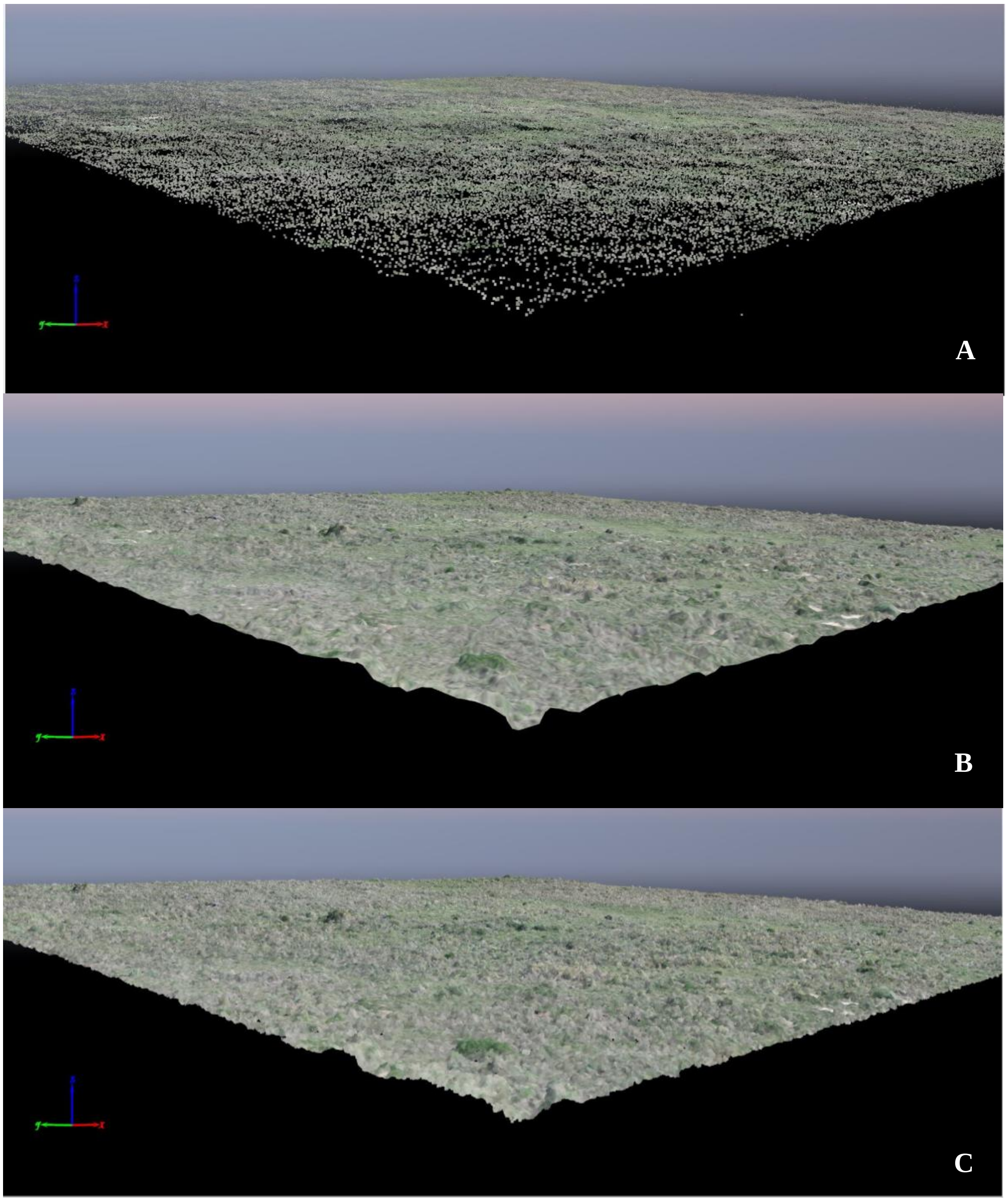
Appendix 1. Hardware and Analytical Specifications for Data Resolution.
(A) The specifications for the camera that was used to capture aerial imagery are shown. Flights were automated with the Pix4D Capture mobile application. Therefore, the auto ISO range and electronic shutter speed were used for all imagery. (B) The Pix4D Capture mobile application in use to automate a flight at a burrow. The flight area was defined as 50 m x 50 m so the core area covered by transects would be quantified at a high resolution. The UAS flew the area at 30 m above ground level with 80% overlap among images to obtain sub-centimeter resolution (0.83 cm/pixel).

A

DJI Phantom 4	*Specifications*
Sensor	1" CMOS Effective Pixels: 20M
Lens	FOV 84° 8.8 mm/24 mm (35 mm Equivalent) f/2.8 – f/11 Auto Focus at 1 m - ∞
ISO Range	Auto: 100 – 3200 Manual: 100 – 6400
Shutter Speed	Mechanical: 8 – 1/2000 s Electronic: 8 – 1/8000 s
Image Size	3:2 – 5472 x 3648 4:3 – 4864 x 3648 16:9 – 5472 x 3078

Appendix 2. Visualization of Spatial Data as Rendered by Pix4D Mapper.

(A) The georeferenced, shared tie points provided the basis for the three-dimensional reconstructions of habitat features. (B) Three-dimensional triangle meshes provided visualization of surface features, but they were not georeferenced. Therefore, triangle meshes were not used for surface data collection. (C) Densified point clouds were used in ArcMap to generate georeferenced, three-dimensional surfaces (triangulated irregular networks).



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