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The Application of Advanced Technologies for Agriculture and Rangeland Management

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THE APPLICATION OF ADVANCED TECHNOLOGIES FOR AGRICULTURE AND RANGELAND MANAGEMENT

A Thesis

by

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ABSTRACT

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This project demonstrates two applications of remote sensing in agricultural and rangeland environments. In the first, an unmanned aerial system (UAS) equipped with a multi-spectral sensor was used to estimate canopy cover across four different cover crop trials at four time periods. In the second, a local database of stationary camera trap images of wildlife was used to train a convolutional neural network to automatically catalogue images by identifying the animal in those images. Both projects aimed to provide an example of how remote sensing platforms and machine learning techniques can facilitate the rapid collection and processing of large-scale field data. In both projects, methods were developed that confirm the utility of advanced remote sensing and computer vision technologies.

DEDICATION

I dedicate my thesis to my parents who have worked tirelessly to instill in me and my sisters the values of perseverance, kindness, and love.

ACKNOWLEDGMENTS

I have been incredibly lucky while at UTRGV and have many people to thank. Thank you to Dr. Rupesh Kariyat and Dr. Christofferson for providing support and cricket skills. Major thanks to Mylen Arias, Jesus Chavana, Mandip Tamang, Amelia Berle, Dr. Jeremy Baumgardt, Dr. John Goolsby, Colin Cain, George Bennack, and Lindsey Richards for providing support and helping me in many ways. I am thankful for the love of my family and friends and for their constant encouragement and guidance. Thank you to Stephanie Kasper, Faeqa Mohsin, and Joy Youwakim for the late-night talks and many adventures. Thank you Mariana for your love and especially for your patience. I would like to thank my committee members Dr. Soti and Dr. Rahman for their support and guidance through this process. I am especially thankful for Dr. Racelis who gave me the opportunity to pursue my interests in sustainable agriculture and technology, for his example in mentoring students with warmth and kindness, and for encouraging us to ask the difficult questions.

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CHAPTER I

INTRODUCTION

Large Agricultural Image Data

Advanced technologies in agriculture are being used to observe conditions of plants, animals, soils, or water across large geographic and temporal scales quickly and without disturbing systems. This becomes especially important in complex, multifactored, and unpredictable agricultural systems. Monitoring, measuring, and analyzing agroecological landscapes is a challenging task, however, deploying new data collection and analysis technologies for large scale agroecosystem management can facilitate this task and better informing management decision by context (Kamilaris and Prenafeta-Boldú 2018). Proximal sensing techniques like those that use unmanned aerial systems, or drones, collect images that provide a more complete picture of agricultural landscapes. Further, large data analysis techniques are becoming an increasingly important research area for classification, anomaly detection, and full-field observation (Teke et al. 2013, Saxena and Armstron 2014). Decreases in the cost of sensors, open-sourced software, and inexpensive computing resources have given way increases in adoption across multiple disciplines (Hunt and Daughtry 2018). Further, state-of-the-art algorithms and the amount of free-flowing information on the internet are further advancing application by making processing techniques more accessible. Large agricultural image data used to inform management practices and develop predictive relationships has become an important component of agricultural research (Kamilaris 2017, Bauer et al. 2019, Chiu et al. 2020). Most notable, these techniques have major potential in capturing complex set of spatial and temporal dynamics within agricultural ecosystems (Tsouros et al. 2019, Tabak et al. 2019). Leveraging big data analytics is an important component of quantifying the impact of management practices in the real-world, in on-farm studies and as implementable tools in the field. Two important advances in the field come from the application of unmanned aerial systems (UAS) for agriculture, and trail-cameras for wildlife management. Both capture large amounts of data that can be used to scout for problems, monitor to prevent losses, and plan for best management practices (Hunt and Daughtry 2018). These two techniques are of particular interest because they capture large scale data that can be processed using state of the art techniques. More so, techniques that use images to extract meaningful information have untapped potential in their ability to address issues in conservation agriculture and rangeland management.

Unmanned Aerial Systems

Unmanned aerial systems (UAS), or drones equipped with sensors have facilitated a major shift in proximal sensing providing data at higher spatial, spectral, and temporal resolutions than ever before. This shift is especially noticeable in agriculture where UAS-based proximal sensing attempts to observe nuance in large-scale complex systems in a way that informs management decisions. Unmanned aerial systems are unique from satellite- or manned aircraft-based proximal sensing because they can fly low to capture high-resolution images, often to collect data multiples times throughout the season, and have become more accessible from lowered costs. Sensors equipped on UAS platforms range from consumer color cameras, to sensors that capture thermal images, to multi-spectral sensors that capture light beyond the visible portion of the light spectrum. Near-infrared (NIR) light is often included in the set of bands (or regions of the electromagnetic spectrum) that come with multispectral sensors and is especially useful because healthy vegetation reflects large amounts. Common applications of UAS in agriculture include the detection of drought, pest, or weeds; assessment of nutrient status; monitoring growth variation within fields; and predicting yield.

Understandably, most applications are used to understand the impacts of management strategies in cash crop systems. Conservation agriculture techniques like cover crops, however, are rarely considered as the main subject of study. Cover cropping is a conservation strategy that employs the use of non-harvested plants in a agroecosystem for a variety of benefits, such as soil improvement, weed control, carbon storage, or biodiversity conservation. Little research exists that uses UAS-based proximal sensing to look at large-scale, on-farm cover crop trials. Large-scale cover crops studies are thus primed for a technique that captures nuances across hectare and better informs complex cover crop management practices. Unmanned aerial systems equipped with multispectral sensors provide a useful approach for collecting high-resolution data that can be analyzed and used to inform management practices. While UAS-based proximal sensing approaches collect data from the sky, other techniques can be used to collect large amount of images data proximally, or from near-by on the ground.

Camera Traps for Wildlife Management

Camera traps, color cameras strapped to trees or fence posts triggered by motion, have shown to be successful and cost-effective for sampling populations of wildlife (Ahumada et al. 2019). Their popularity among conservation organizations has grown dramatically (Steenweg et al. 2017). A common problem among adopters, however, is the stockpiling of uncatalogued images that are collected at a rate that outpaces a person’s ability to sift and label them for the species they contain. A recent survey showed that 61% of camera-trappers (Glover-Kapfer et al.

2019) report image cataloguing and analysis as a major barrier to effective implementation (Ahumada et al. 2019). Unprocessed images make it difficult for conservation projects to gain meaningful insight or inform wildlife management decisions. This major barrier prohibits conservation projects from taking full advantage of an easy to use cost-effective tool. Advances in deep learning, a subfield of machine learning and artificial intelligence, however, have major potential in addressing the issues of camera trap image processing.

Deep Learning

Deep learning goes beyond machine learning by designing models that account for "depth" or complexity in systems. The models are designed in a way that transforms data hierarchically through multiple layers of abstraction (LeCun and Bengio 1995, Schmidhuber 2015). Convolutional neural networks (CNN), a class of deep learning model, take input images and encodes or "learns" the discriminative features of the object in that image. An input image passes through multiple layers that filter, reduce, and pool features. Images dimensionality is reduced but becomes more specific and thus useful in discriminating between classes. The last layer of a CNN takes the concentrated features as input and outputs a single probability for each class. The class with the highest probability determines the prediction. Convolutional neural networks eliminate the need for feature engineering, or the hand-selection identification of characteristics that make an object in an image unique, which is time-consuming and requires expert knowledge. A major disadvantage, however, is the need for large amounts of labeled training data. This poses a major barrier to organizations looking to utilize camera trap data in conservation projects. Deep learning approaches that use camera trap images to train CNNs use enormous datasets of millions of images. Little research has been done that uses local sources of camera trap images to train a CNN to automatically label camera trap images. What is often ignored is the applicability of these techniques to local problems. How can organizations with limited amount of images take advantage of DL techniques? Further, how can communities of camera-trappers and researchers work together to build a library of shareable models trained on local wildlife?

Proximal sensing allows location- and system-specific information to be collected by researchers and conservation practitioners who can use this data in a way that informs decision making and builds on the intuition of key stakeholders. This project aims to connect state-of-the-art proximal sensing and data analysis techniques to researchers and technicians in the field. Further, the aim was not to develop new technologies but transfer well established techniques from the field of computer vision and robotics to conservation.

Images collected by a UAS-multispectral platform and a local database of cameras traps images provided a source of large agricultural and rangeland data which was applied to provide meaningful insight into the impacts of management practices and to develop tools that reduce burden of data processing. In chapter 2, UAS data was used to estimate canopy cover across ~5.2 hectares of on-farm cover crop trials. This project aimed to help researchers collect full-field data of four types of cover crop treatments across four time periods throughout the fall 2019 season. The second project presented in chapter 3 used a local database of camera trap images to train a convolutional neural network that can be used to automatically group images if they have an animal and by species. This project was designed to establish a more efficient data collection techniques for conservation practitioners in the management of nilgia, an exotic ungulate implicated in the spread of a disease carrying tick, the southern cattle fever tick.

I present both of these projects to demonstrate the utility of proximal sensing in informing and improving agricultural management in diverse settings. Both of the projects presented in this thesis are robust pieces of scholarship that when taken holistically, demonstrate how big data and inclusive information can be leveraged to expand the precision of predictions in a way that is both accessible and cost effective. The implications of these works are discussed in chapter 4 and point to new directions of work that have emerged from these projects.

CHAPTER II

UAS-BASED CANOPY COVER ESTIMATION OF ON-FARM COVER CROP TRIALS

Abstract

Canopy cover is an important agronomic plant metrics used to evaluate the efficacy covers crops to provide important agroecosystem benefits. Collecting this data by hand and across large field trials, however, is burdensome, subjective, and susceptible to sampling bias. This study provides an example of how unmanned aerial systems coupled with multispectral sensors can provide high-resolution canopy cover data across large-scale field trials. A UAS-multispectral platform captured images across ~5.2 hectares of cover crop trials in the Lower Rio Grande Valley of south Texas. A Normalized Difference Vegetation Index was applied and used to calculate canopy cover of sunnhemp planted at high and low seeding rates, two cover crop mixes, and a control. The resulting canopy cover field map showed large amounts of heterogeneity across the study area and provided meaningful information about canopy dynamics throughout the season and among management strategies. Sunnhemp seeded at 3 times the prescribed rate did not provided increases in canopy cover and mixes stopped contributing to canopy cover after only 67 days after planting. High resolution data across large areas provided detailed information that has the potential to help researchers, extension agents, and farmers better understand large scale trials.

Introduction

Cover crops, non-harvested plants left to decompose, have been well established for providing a diverse list of agroecosystem services. They protect soil from water and wind erosion (Dabney et.al. 2001), suppress weeds and pests (Creamer 1996; Teasdale 1996), increase soil organic matter via decomposition (Steenweth and Belina 2008), remediate soil compaction (Williams and Weil 2004), attract beneficial insects (Zang 2007), and enhance nutrients for cash crops (Tonitto 2006). Cover cropping as an agronomic practice has grown considerably in popularity with farmers planting more cover crops than previous years (CTIC 2017). Effective cover cropping over the short-term, however, is highly nuanced and like many conservation practices is knowledge intensive, relying on regionally specific information that determine best-use management practices. Determining the proper cover crop, as either a stand-alone or mix of species, involves looking at their effectiveness in addressing the specific concerns of farmers.

Participatory research is an especially valuable approach that allows researchers and farmers to work jointly using field-scales similar to those in farm operations. Applications and results from these studies are valuable for farmers, key stakeholders in design and management practices, and for researchers who are given the opportunity to study the diverse impacts in real-world agroecosystems (Jackson et al. 2004). However, observing basic plant traits across large scales and throughout the growing season is a difficult task. Fractional canopy cover (CC) is one such trait that has been related to weed suppression (Stivers-Young 1998, Creamer et al. 1996) in cover crops. Manually collecting CC data, however, is time consuming, biased by sampling design, and fails to capture the in-field crop variation often found in experimental studies. The weight of these downsides increases with scale. Collecting data across large-scale field trials without sacrificing resolution thus becomes increasingly important in evaluating cover crops

Recent advances in proximal sensing and cost-effective sensor technology have made it possible to collect full field high-resolution data.

Proximal sensing offers an efficient way of mapping large extents of agriculture plant data (Ashupure et al. 2019). An extensive body of work exists that shows satellite and manned aerial sensor platforms successfully used to capture large-scale agronomic data (Scharf and Lory 2002, Sripada et al. 2006, Trout et al. 2008, Kyveryga et al. 2012, Melin et al. 2017). However, the lack of spatial resolution associated with these coarse-grained data products, in addition to limited revisit times (temporal resolution), and high costs, preclude its use for finer grade resolution required for farm-scale applications.

Unmanned aerial systems (UAS) that couple consumer grade sensors with commercially available proximal-controlled drones overcome the limitations of satellite- and manned aircraft-based proximal sensing. Flying low offers finer resolutions, lighter portable platforms give way to more frequent flights, and an expanding market has lowered costs. Applications using UAS have shown significant utility in agricultural systems including soil mapping and assessment of nutrient needs (Lopez-Granados et al. 2005), irrigation monitoring and scheduling (Meron et al. 2010), assessing crop ground cover (Rajan et al. 2014) and monitoring stress indicators stress indicators. UAS-based leaf-area index (LAI) estimation have been applied in crop phenotyping (Makanza et al. 2018), yield estimation (Feng et al. 2020), and crop monitoring (Tu et al. 2019). Most importantly, a growing body of work has emerged that applies UAS-based CC estimations to detect the effects of no-till on cotton (Ashapure et al. 2019, Ashapure et al. 2019), to predict cover crop biomass (Roth and Streit 2017), and to measure canopy structure in orchard systems (Tu et al. 2019). Multispectral sensors play an important role in accurately estimating CC because they capture near-infrared (NIR) light which is highly reflected by vegetation. NIR is necessary to create the normalized difference vegetation index (NDVI) that exploits differences in the reflective properties of vegetation and non-vegetation. It is thus an essential component in differentiating canopy from soil. NDVI-based CC estimations have been shown to be the most stable across changing environmental conditions and is consider the most reliable technique to measure CC (Rouse et al. 1974).

Despite being an effective tool, the use of UAS-based CC estimations in cover crop research is relatively uncommon. Roth and Steit (2017) used CC as a predictor of biomass and not as a source of evaluative data. While Ashapure et al. (2019) used it to detect the effect of tillage practices on cotton. There is much potential in the use of this technique to reduce sampling bias, subjectivity, and burden in collecting full-field data. This study presents an example of how UAS-based proximal sensing was applied to collect agronomic data across large-scale field trials and throughout the growing season. A UAS platform equipped with a multispectral sensor captured aerial images of four cover crop treatments and a control across four time periods. Canopy cover data alone is insufficient to evaluate efficacy of cover crop management strategies. This study considered CC as one of many important factors that should be considered when used to determine proper cover crop management strategies.

Methods

Study site

This study was conducted in Hidalgo County, Texas where data was collected during fall 2019 as part of a larger multi-year cover crop trial. The experimental design was replicated and randomized on ~5.2 hectares of non-irrigated Willacy fine sandy loam. An onsite weather station recorded 120.20 mm of rainfall from September 25th to December 17th with the largest single rain event (39.7 mm) occurring on November 11th, 2019 (Kasper et al. 2019). Five treatments –

two single species cover crops, two multispecies mixes, and one control - were replicated five times. Single species treatments were seeded at two different rates shown in Table 2.1. Each of the five experimental blocks contained five sub-plots. Each sub-plot was 70 m long and 1.02 m wide shown in Figure 2.1. Subplot boundaries were created by taking four sub-centimeter GPS points at each plot corner. Cover crops were planted on September 18th, 2019 using a sunflower seeder and terminated on December 15th, 2019 using a roller-crimper.

Data Collection and Preprocessing

As a FAA certified UAS pilot, I flew four flights opportunistically within two hours of noon on sunny days. A DJI Matric 600 Pro (SZ DJI Technology Co., Ltd., Shenzhen, China) was used as the proximal-sensing platform and carried a Slantrange 4p+ multispectral sensor (Slantrange Inc, San Diego, CA). The sensor included an integrated incident light meter for frame-to-frame, radiometrically adjusted reflectance measurements (Ashapure et al. 2019). Images were captured in the blue, green, red, and near-infrared (NIR) bands. Ground control points were placed across the study area, were captured at each flight, and surveyed using a post-processed kinematic (PPK) GPS system (Reach RS+ Emlid Ltd., Hong Kong, Hong Kong).

The UAS flew autonomously along a pre-planned flight path at a speed of 4 m/s, took images every ~0.9 sec, and all but one flight was flown at ~88 m above ground level (AGL) achieving a ground sampling distance of ~1.5 cm (Table 2.2). The flight on November 11th was flown at 106m AGL. The speed of the UAS and rate of image capture created an image end-lap and side-lap of 75%. Flight heights were chosen to maximize spatial resolution while covering the full-field. Battery times, weather, and area had to be taken into account.

Two software services were used in the aerial triangulation and ortho-mosaic generation processes: Slantview (analytics.slantrange.com) and Agisoft (Agisoft Metashape Professional

1.6.1, Agisoft LLC, Russia). Slantview, the sensor company's proprietary software, applied its proprietary radiometric calibration adjustments to the raw images. Agisoft, a standard among drone-based imagery processing, was then used to stitch or ortho-mosaic the calibrated images. Coordinate information of ground control points were used to reinforce the ortho-mosaic construction process, a standard procedure that improves end-product accuracy.

Canopy Cover Calculation

Further image processing and analysis was done with the open-sourced Quantum Geographical Information System (QGIS 3.4.10, QGIS Development Team, Raleigh, NC, USA) software. The multi-band ortho-mosaic was used to calculate canopy cover percentage across study sites. A sampling grid of 6,830 cells per subplot was overlain on the multiband ortho-mosaic and each grid cell (0.25 m^2) was used as a sample location for CC calculation. Normalized difference vegetation index (NDVI) was calculated from the multiband ortho-mosaic and created for each capture event. The NDVI results were visually inspected for a thresholding value separating canopy from soil. This thresholding value was then used to create a binary image where 0 represented non-canopy and 1 represented canopy (Ashupure et. al. 2019). This binary image was used to calculate canopy cover by taking the percentage of vegetation in each grid or sampling area (Figure 2.2).

Results

Ground Truthing CC

Ultra-high-resolution imagery was taken and used to ground truth lower resolution CC estimations. Images were taken from altitudes ranging from 18m to 30 m above ground level (AGL) which provided a ground sample distance of 0.38 to 0.58 cm/pixel. Low altitude images were taken of the eastern 1.2 hectares and included all treatments. CC estimations were calculated on 30m AGL imagery using the same methods and results were compared by plotting the average of each sampling area. CC estimation were compared, and calculations followed a one-to-one comparison between the two heights plotted as a straight line resulting in a Pearson's correlation r value of 0.9799 (Figure 2.3). Future work should investigate the difference of CC captured at both heights. R values for October 26th, November 16th, and 24th, were 0.6642, 0.6855, 0.7458 respectively. The lower correlation values during the beginning of the season were likely due to smaller amounts of canopy cover.

Treatments effect on canopy cover

The CC field maps (Figure 2.4) shows considerable in-field heterogeneity in all four capture periods and an increase in CC as the season progressed. Summary statistics computed by taking mean CC of each subplot the means of subplots cells values show CC steadily increased, as expected, for all treatments across the four time periods. General trend of each treatment throughout the growing season show M1 with the highest amounts of CC throughout the season and leveling off after the 24th.

A two-way mixed ANOVA was used to compare the means of CC cross-classified by treatment and time. Results indicated significant interactions among treatments and within time periods. Multiple pairwise comparisons were made to determine which treatments were different from another and within-subject time variable at each level of treatment (Figure 2.5 and 2.6).

Various patterns emerged as CC was compared among treatments throughout time (Figure 2.5). As expected, 38 days after planting (October 26th, 2019) all treatments had significantly more CC compared to the control while cover crop treatments were not significantly different from another. Treatment M1 had significantly more CC than other treatments for the second, third, and fourth capture events. The mixes were only different for capture event three (November 24^{th}, 2019) where M1 was significantly higher than M2. Most striking is neither sunnhemp treatments differed despite a 250% increase in seeding rate.

When looking at the progress of treatments throughout time, mixes and sunnhemp treatments behaved differently during the growing season (Figure 2.6). Neither of the mixes increased significantly after the third capture event (67 days post planting) while sunnhemp treatments did. Sunnhemp was slow to significantly increase in the early part of the season, however, continued to increase when the mixes did not. M1 and M2 made no significant improvements in canopy cover past November 24^{th}.

Discussion

This project used UAS-based proximal sensing data to estimate canopy cover of four cover crop treatments across 5.2 hectares. Results showed M1, dominated by radish, was the most successful at generating large amounts of CC in a short amount of time. Results also verified industry standards that increased seeding rate in sunnhemp does not increase canopy cover. More is not better in this case. Canopy cover in mixes did not increase beyond 67 days after planting and found sunnhemp treatments, while slow to increase CC in the first half of the season, continued to increase when mixes stopped.

Soil Moisture

The ability to develop high amount of CC quickly and evenly throughout the field is an important factor to consider in understanding the effectiveness of many crops. CC, however, is one of many agronomic characteristics and when used alone does not fully capture the impact of management decision and nuance of complex agroecological system. Various sources of information and agronomic data should be used to inform decisions and evaluation management practices. Twenty-five in-ground moisture sensors placed at the cash crop root zone recorded data throughout the study period. The collected data showed that cover crops did more to remove soil moisture while control (CO) treatments retained it throughout the season (Kasper et al. 2019). Further, moisture data collected on December 7th, 2019, the same day as the last UAS flight, was compared to UAS-estimated CC data. A Pearson's correlation coefficient of -0.776 showed a negative relationship between canopy cover and soil moisture. The large canopy and root system of M1 and M2 used more moisture even after rainfall events (Figure 2.7). This aligns with the concerns of area farmer's that cover crops take important soil of moisture from the preceding cash crop. Cover crops that create large amounts of CC and as a result provide benefits, like suppressing weeds and add soil organic matter, do so at the cost of leaving less moisture for the preceding cash crop. Further research is needed to investigate the relationship between canopy cover, moisture, and their role as proxies in identifying successful conservation management practices.

It should be noted that this project did not directly calibrate for reflectance. An onboard incident light sensor was used to account for changes in irradiance during flight and was applied during the initial processing steps. Software developed by the sensor company applied proprietary reflectance corrections. While attempts were made to gather information about the applied correction, future work should consider the integration of other radiometric calibration techniques like reflectance panels or the use of spectrometer-based ground truth samples. Additional steps were taken to improve data collection process and account for incoming light including flying within two hours of solar noon, surveying 5-15 ground control points with sub-centimeter RTK GPS, applying front and side overlap of 75%, and flying only under clear sky conditions. While these steps were considered sufficient for the rough binary segmentation that was used to discriminate vegetation from non-vegetation, resulting NDVI values could be affected by the changing atmospheric conditions throughout the season. Further calibration steps should be used for problems that require the precise application of reflectance values such as land cover classifications or NDVI-based health assessments. Further work should be done to compare canopy cover estimations with and without the various forms of radiometric calibration that can be performed on UAS-based imagery. A thorough overview of the best practices for UAS multispectral sensor calibration can be found at Assmann et al. (2018).

Conclusion

This project proved to be useful in establishing the potential of UAS-based proximal sensing for providing CC estimations across large-scale cover crop trials. High-resolution data was captured by a multirotor UAS-sensor platform and applied to identify differences in CC among various cover cropping management strategies throughout the fall 2019 growing season. Multispectral sensor-based CC estimation provided useful information across 5.2 hectares of cover crop trials and accurately capture in-field heterogeneity often ignored through traditional by-sight CC estimations. Results showed that a mix made up of mustard, radishes, cowpea, and sunnhemp created the most CC which was expected given its morphological characteristics. Canopy cover estimations also showed that there were no differences in CC between sunnhemp varieties despite SH45 having 250% higher seeding rate. More is not better in this case. Further, results showed found that CC increased differently for the two types of treatments. Sunnhemp varieties continued to increase CC beyond 67 days post-planting while mixes did not. Taken with other sources of data, CC estimation via UAS-based proximal sensing provided information regarding the CC in various cover crop management strategies. My goal was to provide a simple example of how UAS-based proximal sensing could be applied to cover crop research adding to the broader body of information that is used to evaluate the efficacy of cover crops.

Opportunities and Challenges

UAS-based proximal sensing in precision agriculture is a new and exciting field. Despite the rapid improvements in sensor and drone technology, the process of collecting image data and turning it into actionable information continues to be a challenge. An understanding of the most relevant products on the market, flight controller and sensor systems, various pre-and post-processing software, and experience working with geospatial systems is needed.

Major issues involve the lack of standardized workflows for image collection and pre- and post-processing of data. Advance knowledge and familiarity with products is needed to integrate sensors to payloads. and advances in technology and lowered costs A few major drone companies have The explosion of affordable drones, sensors, and associated tools has created a in that applies advanced UAS and sensor technologies to the collection of field-scale data.

Tables and Figures

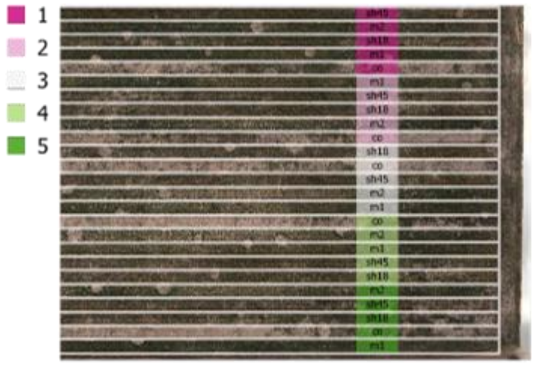
Table 2.1 Cover Crop Treatment Information

Treatment				Seeding Rate (kilo./ha)	
	Abbreviation	Common name	*Genus species*	Single species	Mix total
Sunnhemp	SH18	Sunnhemp	*Crotalaria juncea*	20.2	
Sunnhemp	SH45	Sunnhemp	*Crotalaria juncea*	50.4	
Mix 1	M1	Mustard	*Brassica juncea*	22.4	
		Tillage radish	*Raphanus sativus*	22.4	
		Cowpea	*Vigna unguiculate*	19.1	
		Sunnhemp	*Crotalaria juncea*	19.1	
					82.9
Mix 2	M2	Tillage radish	*Raphanus sativus*	11.2	
		Hairy vetch	*Vicia villosa*	11.2	
		Black oats	*Avena strigosa*	5.6	
					28
Control	CO	No cover crop			

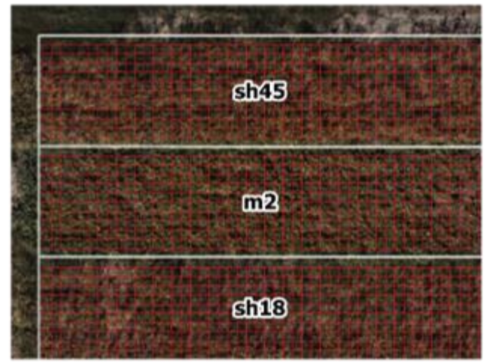
Table 2.2 UAS Flight Information

Date	Flight Altitude	Peak Overlap (%)	Ground resolution (cm/pix)
10/26/2019	18	75	0.38 cm/pix
10/26/2019	88	75	1.83 cm/pix
11/16/2019	28	75	0.58 cm/pix
11/16/2019	106	75	2.22 cm/pix
11/24/2019	26	75	0.54 cm/pix
11/24/2019	88	75	1.82 cm/pix
12/07/2019	30	75	0.56 cm/pix
12/07/2019	88	75	1.84 cm/pix

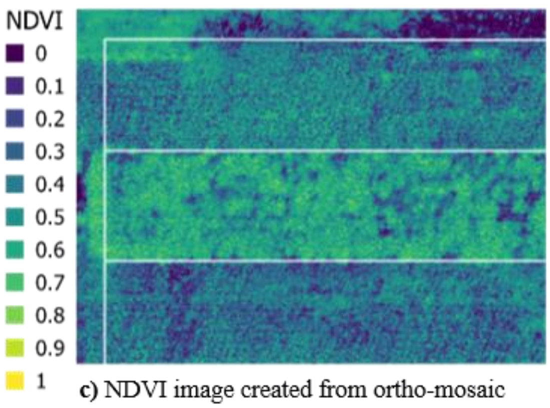
Figure 2.1 Experimental Setup and Study Site



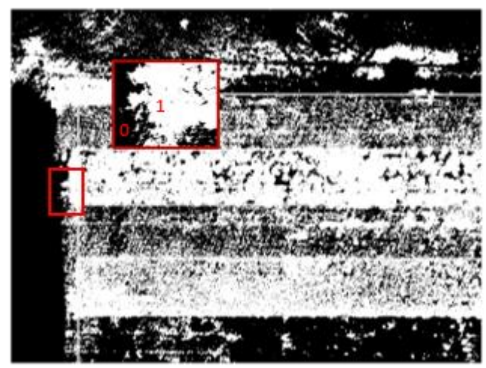
a) Six-band ortho-mosaic constructed and treatment design.



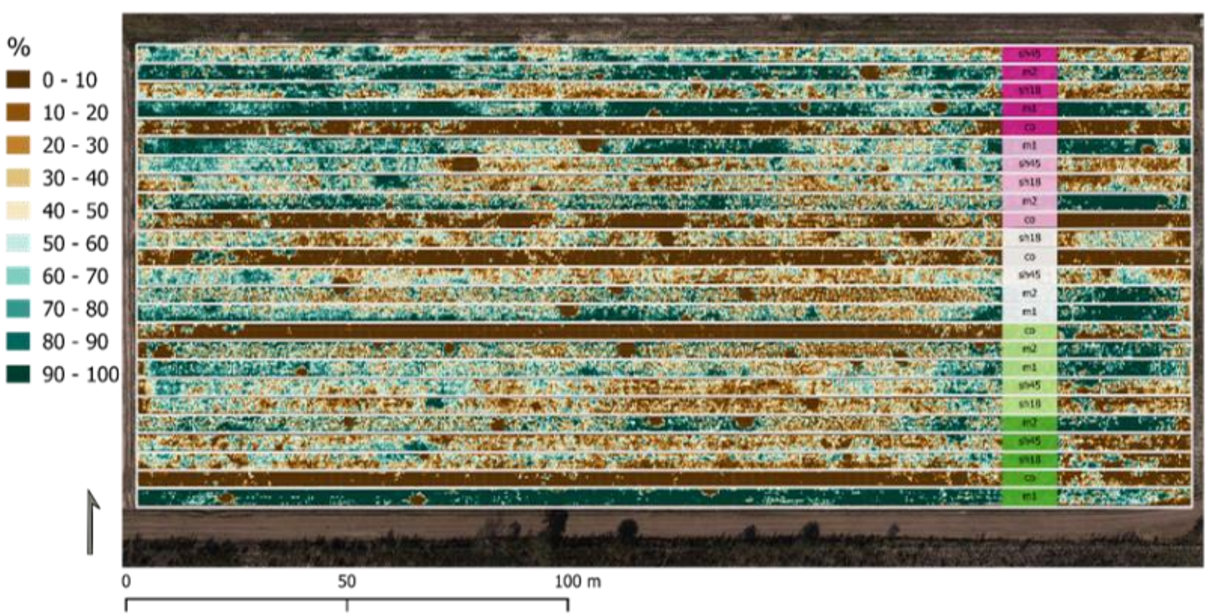
b) Total of 170,750 0.25 m2 sampling gird. Each plot contained 6,830 sampling grids.



c) NDVI image created from ortho-mosaic and used to gather thresholding value.



d) Binary image was created using NDVI thresholding value of 0.4 that delineated vegetation (1) and non-vegetation (0).



e) Resulting canopy cover map for December 7th, 2019.

Figure 2.2 Data Processing Workflow

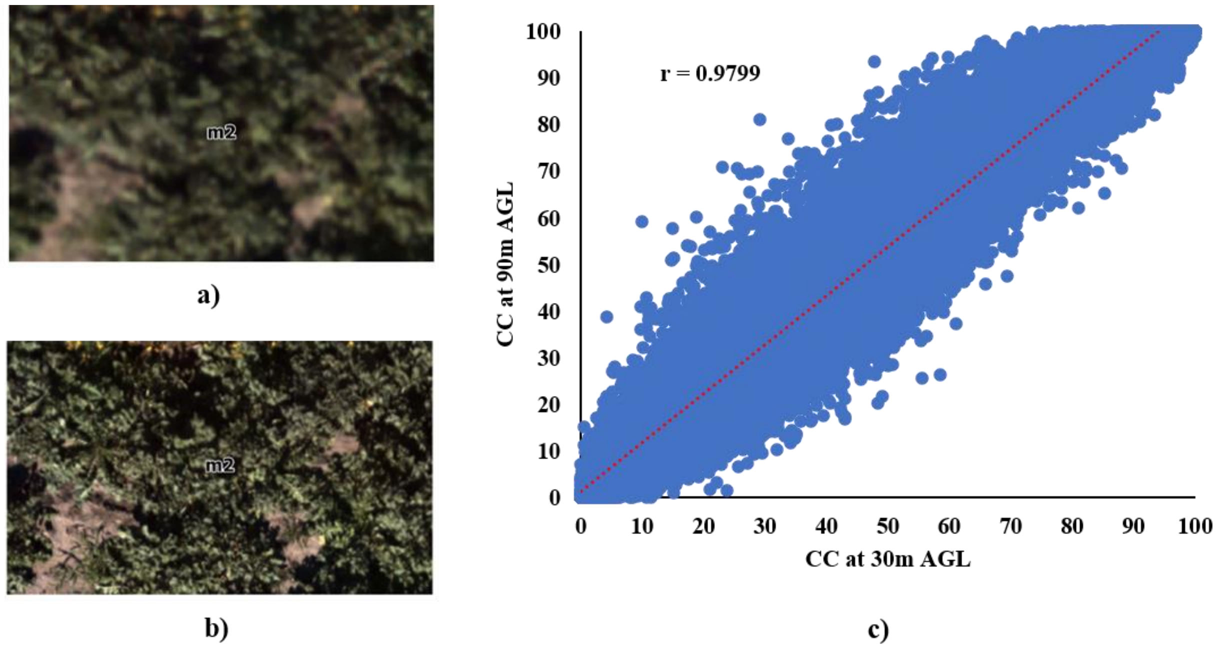


Figure 2.3 Correlation Between Ground Truth and Sampled Values of Canopy Cover

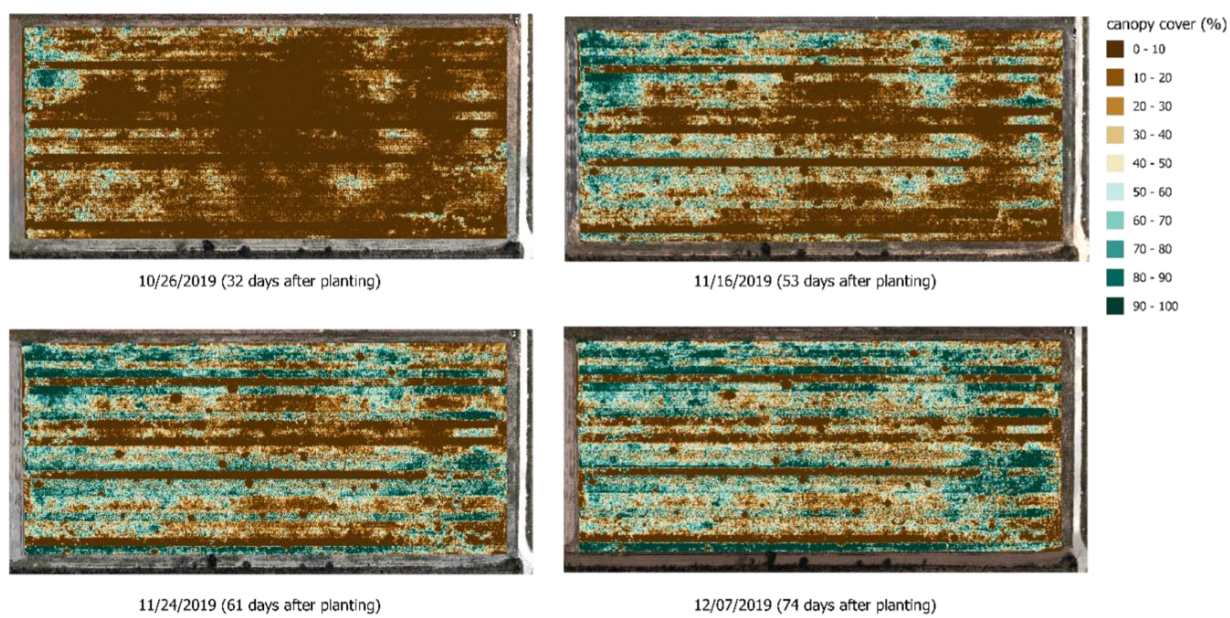


Figure 2.4 Canopy Cover Field Maps

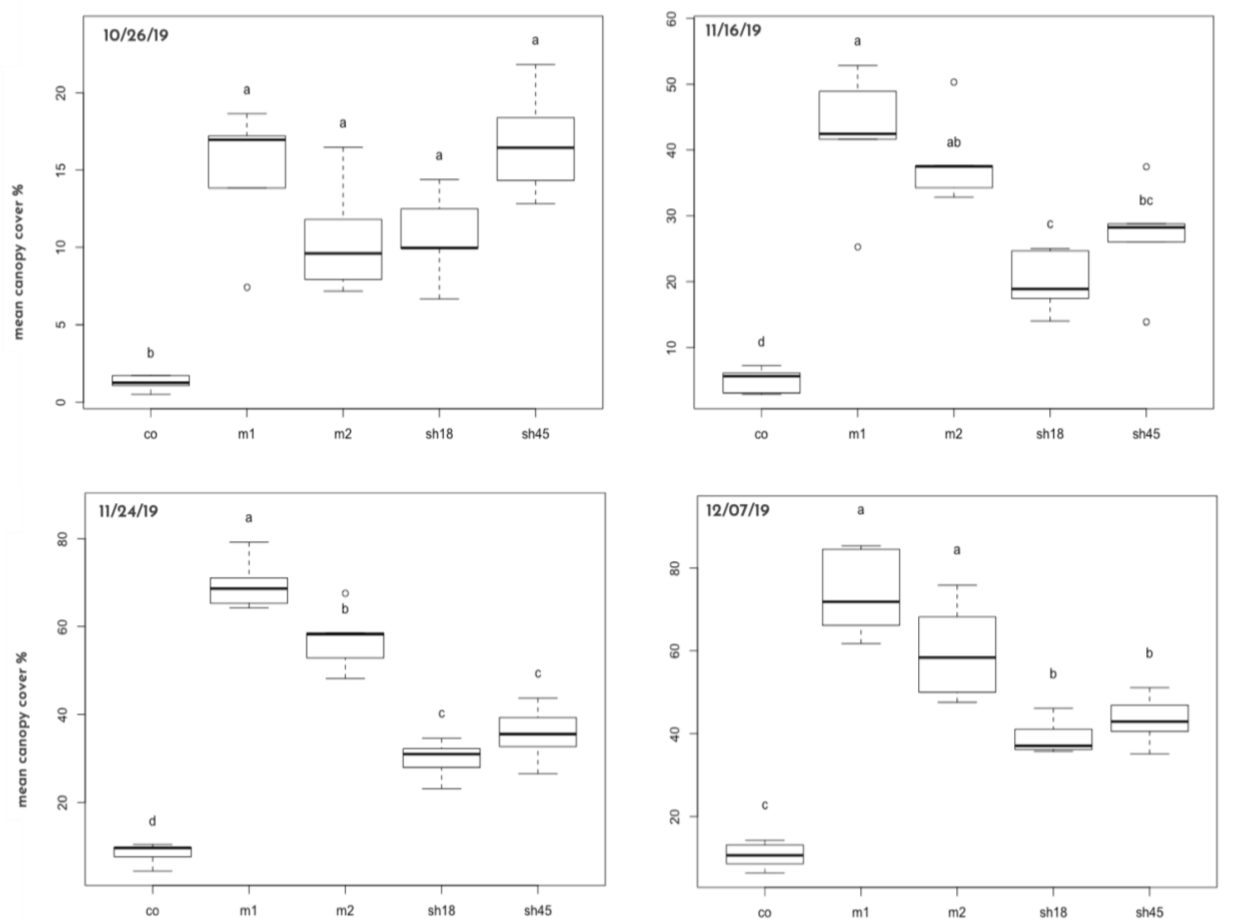


Figure 2.5 Comparing Canopy Cover Between Treatments

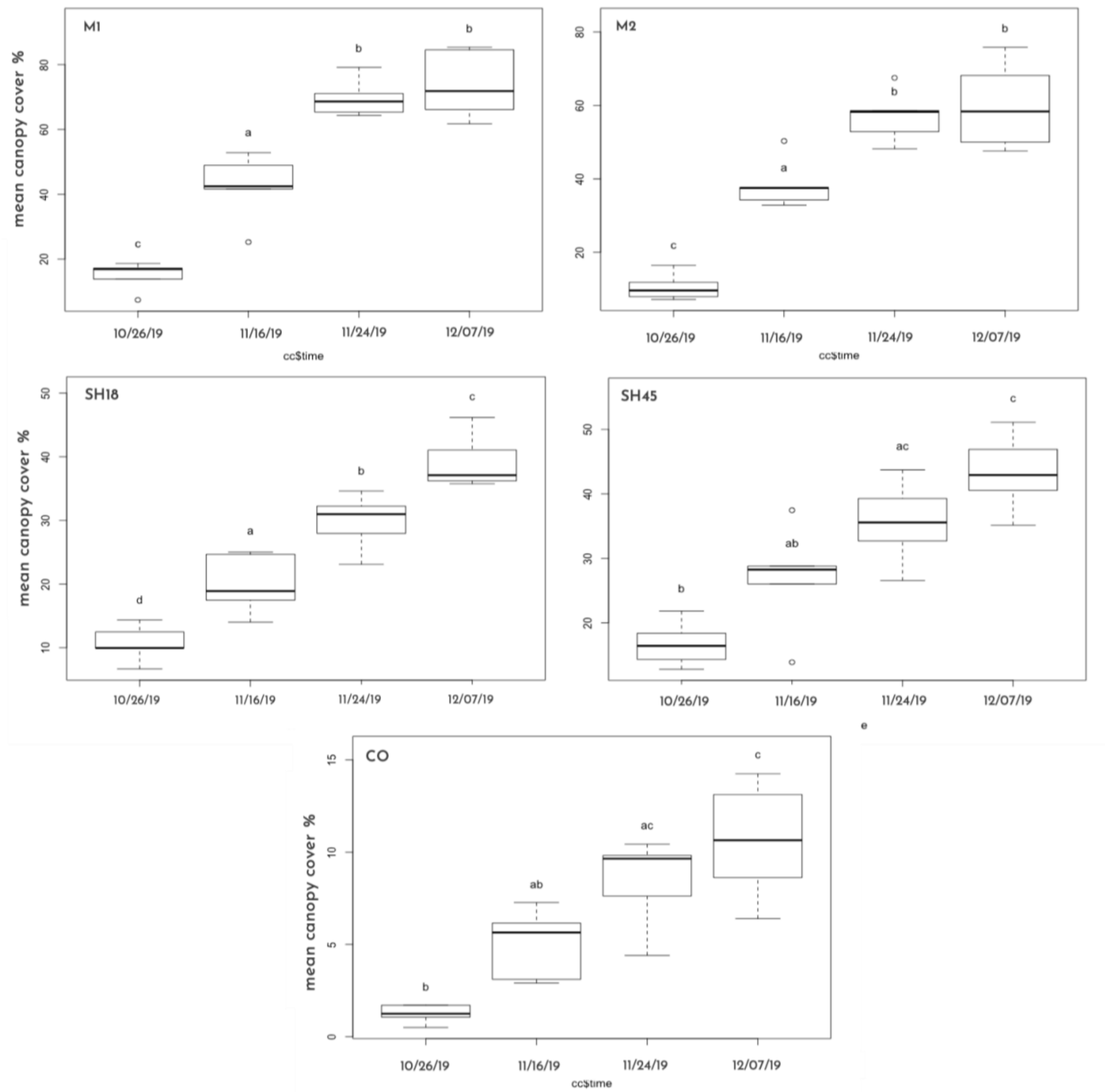


Figure 2.6 Comparing Individual Treatments Throughout Time

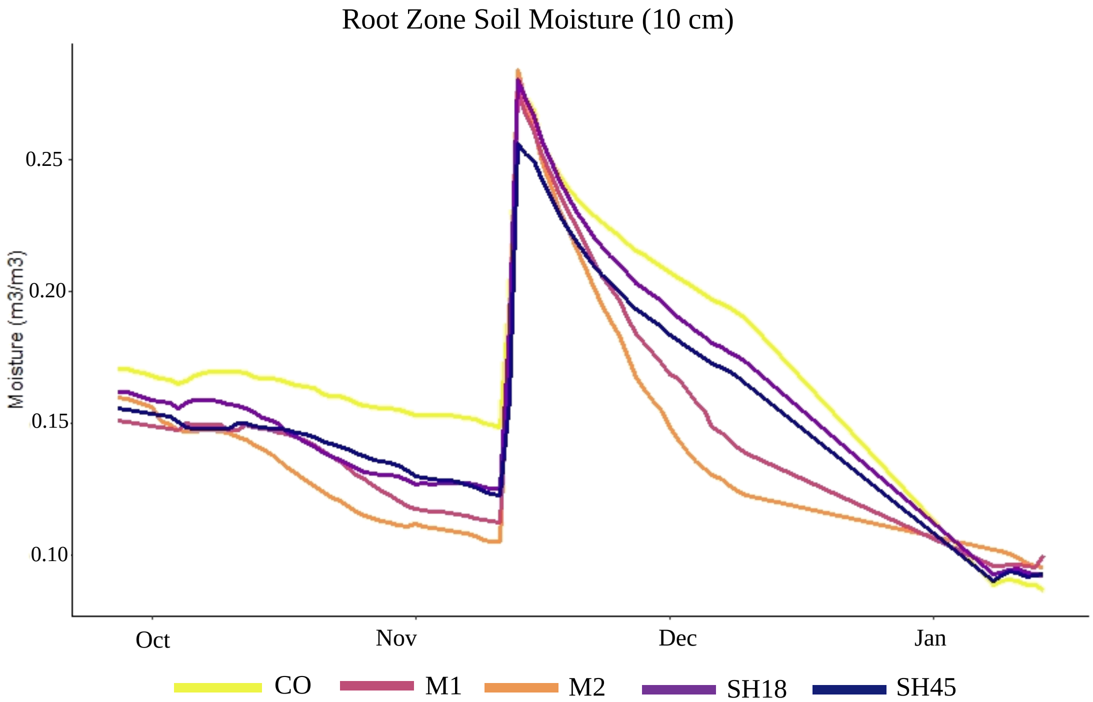


Figure 2.7 Root Zone Soil Moisture

Adapted with permission from Kasper et al. (2019).

CHAPTER III

AUTOMATIC CAMERA TRAP CLASSIFICATION USING ANIMAL-SPECIFIC TRANSFER LEARNING FOR NILGAI MANAGEMENT

Abstract

Camera traps provide a low-cost approach to collect data and monitor wildlife across large scales. Hand-labeling images at a rate that outpaces accumulation, however, becomes increasingly difficult. Various studies have shown that deep learning and convolutional neural networks (CNN) can automatically classify camera trap images with a high degree of accuracy. Training CNNs, however, depend on large amounts of data and advanced knowledge in computer programming. Examples were given to show how a small dataset trained using transfer learning can drastically reduce the number of labor hours of hand-labeling camera trap images. CNN was trained to identify two groups, "Nilgai" a non-native game animal and "not nilgai", with an overall accuracy of 97%. A second model was trained to identify 21 classes with an overall accuracy of 89%. This approach trained a model that could potentially reduce large amounts of labor hours needed to hand-catalogue camera trap images.

Introduction

Camera traps, wireless cameras placed on trees or fence posts activated via motion sensors, have been an important tool for wildlife studies. They have been used to estimate population densities (Howe et al. 2017), create species lists and inventories in dense tropical environments

(Srbek-Araujo and Garcia 2005; Azlan 2006; Tobler et al. 2008), understand population size and distributions (O'Connell et al. 2010), and identify new species (Rovero and Rathbun 2006). Their relatively low-cost and ease make them scalable across large geographic regions. A common problem, however, is the rapid accumulation of images that outpace one's ability to sort and label them (Swanson et al. 2015; Niedballa et al. 2016). When silos of images go unprocessed, valuable information is lost or goes unused to its potential. To address this issue state-of-the-art deep learning techniques, a subfield of machine learning, has been identified to automatically recognize what species is in an image and label them appropriately (Gomez et al. 2016, Norouzzadeh et al. 2018; Tabak et al. 2019; Willi et al. 2019). Studies that demonstrate this, however, rely on enormous datasets like Snapshot Serengeti (~7 million images) (Swanson et al. 2015) or the North American Camera Trap dataset (3.3 million) (Tabak et al. 2018) that require robust computational resources.

Given the widespread application of camera traps and the high-demand for an image labeling tool by conservation practitioners, my aim was to demonstrate by example how open-sourced tools, pre-trained models, and a small but diverse dataset of 120,000 images can be used to train a CNN. Unlike previous studies whose pretrained model depends on ImageNet data, this example leveraged nature-specific pretrained models to train on a small dataset. The model was initially trained by Cui et al. (2018) first on ImageNet data then on iNaturalist data and acted as a base to further train a south Texas specific wildlife classifier. More specifically, a local database of camera trap images was used to demonstrate the capabilities of 1) a binary classifier that discriminates between a single species of interest and "other" and 2) a multilabel classifier for 21 groups - 20 animal species and one "none" group.

Methods

Study Area

This study was meant to provide tools that wildlife managers could apply to build an automatic image labeling tool that detects nilgai antelope *(Boselaphus tragocamelus* (Pallas)), an exotic bovid with expanding populations in deep south Texas. Image data was collected from twenty-five motion-sensitive cameras placed in areas of known wildlife activity in Cameron county in the Lower Rio Grande Valley of Texas from 2018 to 2019. This county is along the international border characterized by a mosaic of shrubby plants, mesquite, and semi-arid vegetation. Free ranging nilgai native to the Indian subcontinent were introduced into these areas in the 1930s (Leslie 2008). Although there appears to be no competition with other native species (Schmidly 2004), nilgai inhabit areas that support federally listed endangered species of interest and worth monitoring such northern populations of ocelot (*Leopardus pardalis*) and perhaps the Gulf Coast jaguarundi (*Puma yagouaroundi cacomitli)* (Leslie 2008). Furthermore, recent studies reveal that nilgai are optimal hosts for the southern cattle-fever tick, *Rhipicephalus microplus (Cannestrini),* and have exacerbated current efforts to eradicate this exotic pest of wildlife and livestock (Lohmeyer et al. 2018). As such, monitoring nilgai behavior, population, and distribution have important implications for both wildlife management and agriculture in the region (Foley et. al. 2017; Goolsby et al. 2019).

Image Data and Preprocessing

Images were drawn from a local database part of a multi-year field research aimed at treat cattle fever tick-infested nilgai at fence crossings. They were hand-labeled by research technicians with advanced experience in recognizing animals of interest. Images were labeled using the open-access Colorado Parks and Wildlife Photo Warehouse, a custom Microsoft

Offices Access application designed specifically to store, manage, label, and analyze wildlife camera trap data (Ivan and Newkirk et al. 2016).

We created three types of datasets necessary for training deep neural networks: 1) a large *training set* (~85% of total images) for model learning, 2) a smaller *validation set* (~5% of total images) for frequent testing and adjustment of model settings, and 3) a *test set* to evaluate the final trained model (~10% of total images). Because two classifiers were trained, separate train, validation, and test sets were created for each.

Balancing Training Set

A balanced training set contains an even distribution of images across each group. The original raw image set of more than 2.5 million images, however, was highly imbalanced with 84% (~2 million images) having no wildlife which was labeled as "None". Camera trap data is often imbalanced because of false capture events that occur from a sensor being easily triggered by wind, grass, or other non-target objects. Training on imbalanced data is problematic since models can favor groups with more examples while ignoring those with only a few (Norouzzadeh et al. 2018). The model could simply guess "None" for most images and still result in a high overall accuracy. To correct the imbalance, the training set was oversampled or sampled with replacement (He and Garcia 2009) so each group had roughly the same number of images. For example, if the "Dog" group only had 50 unique images, each was copied until the total number of images matched that of the most frequent occurring group. This oversampling technique, however, has its drawbacks. Since images in rare groups are repeated often, the model lacks the robustness to generalize on new examples in the future. This might be an issue for conservation projects that use camera traps to capture endangered species that are important to monitor but rarely occur. In this case, however, species with rare classes were considered less important for classification and specific management objectives. The most important group, “Nilgai”, was one of the most frequently occurring.

Still, to reduce the number of copies for oversampling, the total number of images was lowered from 2.5 million to 120,000 by taking slightly more than the next most frequent group “Human” which represented signs of human activity. Additionally, a dataset of 120,000 images instead of 2.5 million provided benefits beyond class balancing. Training times went from weeks to days and replicating a scenario closer to what conservation practitioners experience. Access to 2.5 million labeled camera trap images of local wildlife is rare. Data was further altered by either combining or eliminating groups. Four groups were combined – “Feral cat”, “Ocelot”, “Bobcat”, and “Exotics, other” – as “Cat” while “Unknown” and “Squirrel” were eliminated. These groups either lacked sufficient examples or were mislabeled (e.g., an image of a “Bobcat” was labeled as “Ocelot”).

Training sets for both models consisted of 100,000 images of balanced classes while validation and test sets were unbalanced. It should be noted that a single camera capture event consisted of three images taken in rapid successive order and contributed to the total dataset size and class count.

We applied four types of data augmentation, a technique commonly used to strengthen model predictions by slightly altering images for each training cycle. Images were rotated, shifted, sheared, and flipped both horizontally and vertically. This procedure is done for each training epoch and randomly for each image. Preprocessing also included rescaling pixel values between 0 and 1 and resizing the image from 2,048 x 1,152 to 299 x 299 pixels – standard procedures done to reduce the computational expense of training. A sample of camera trap images for the top-7 most common classes can be seen in Figure 3.1.

Deep Learning

Deep learning, a subfield of machine learning, aims to extract information from large-scale data by learning from successive layers of increasingly meaningful representations called *features* (Chollet 2018). A deep learning model, typically a *neural network*, is made up of many layers and contribute to its depth. A neural network organizes layers and is trained on labeled data to learn important features which are stored and used to make predictions on unlabeled data. A CNN, a class of neural networks, is designed to learn three-dimensional input data like images and has two main parts: a base made of *convolutional layers* and a classifier known as the *fully connected* layer (FC). Convolutional layers apply filtering and pooling operations that distill input data to its defining features that ultimately inform the final classification results. This multi-stage transformation process is parameterized by *weights*, stored filter values that extract features. Learning occurs by adjusting these weights in such a way that the model maps input data to its correct label. As images pass through a CNN, weights are initialized, and features pass from one layer to the next going from simple to more complex. The early layers are trained to react strongly to simple features like edges, lines, and sharp color gradients. Following layers use cues from the previous to extract more advanced features. This process occurs until the feature outputs of the last convolutional layer are flattened to reduce computation and serve as input data for the FC. Here, the FC infers the probabilities of input features where a particular class like "Nilgai" or "Deer" is decided. The network takes the predicted versus actual label to calculate an error score which is propagated back throughout the network to adjust various filter values or weights. High intensity output values shown in yellow in Figure 3.2 represent the extracted features. The first shallow layers highlight edges and changes of color in fur while final layers are more complex and difficult to interpret.

In practice, CNNs are rarely trained from scratch from a lack of sufficiently large dataset and/or computational resources. Instead, an approach especially useful for small datasets called *transfer learning* is applied that transfers knowledge gained from training a model on large-scale generic data which then acts as a base for future learning on more specific tasks. Knowledge is transferred in the form of saved weight files that contain weight parameters, complete or partial model architectures, and model settings. They are portable, can be easily downloaded from open-source libraries, and loaded into a new training instance. The portability of learned features across different problems makes this approach highly effective for small-data problems (Chollet 2018).

Pretrained models can be used in two ways: as a *feature extractor* and for *fine-tuning.* Feature extraction involves training only a newly added fully connected layer using examples of new images. The convolutional portion of the network is *frozen* – preventing weights from being updated during training - and representations learned in the original model extract features which are then used as input into a newly added fully connected layer. Feature extraction takes less time and computational resources and is a necessary step for fine-tuning. Fine-tuning involves jointly training the unfrozen convolutional base and the newly added fully connected layer. This process slightly adjusts convolutional layer weights of the model making it more specific to the problem at hand. Feature extraction must occur first since the trained fully connected layer restricts weight adjustments from being too large which would drastically change and eliminate feature representations learned from pretraining (Chollet 2018).

We looked to previous work done by Cui et al. (2018) who used a large dataset and transfer learning to classify images of plants and animals. They first trained a model on ImageNet data which is comprised of 1,281,167 images of 1,000 common every-day objects and widely used in transfer learning (Cui et al. 2018). The model was then trained on iNaturalist 2017 dataset (iNat) which was made up of 579,184 nature-specific objects (insects, mammals, amphibians, etc.) (Cui et al. 2018, Vanhorn et al. 2018). The iNat data was taken from www.inaturalist.org, collected and verified by citizen scientists, and originally described in Van Horn et al. (2018).

This approach leverages the accumulated knowledge of previous training instances by applying the pretrained model as a feature extractor and for fine-tuning. A model pretrained on larger, generic datasets was used to refine classification results by training on a smaller but domain-specific dataset of south Texas wildlife (Figure 3.3).

Training and Evaluation

The model was trained using the InceptionV3 model architecture (Szegedy et al. 2016) - defined by its unique sequence and type of layers. Transfer learning was applied by loading iNat weights, froze the convolutional layers from updating its filter values, and retrained the model on a fully connected layer customized to the unique number of classes. After each training cycle (epoch), the validation set was used to monitor performance and adjust model settings, known as *hyperparameters*. For the second part, the trained model was fine-tuned by unfreezing convolutional layers and allowing all ~21-million weight parameters to be updated. This process was done for both the multi-label and binary classifier. The model was evaluated on the validation set throughout the training process and after making adjustments.

After training and model adjustments were made, the test set was used to evaluate prediction results – the number of true positives (T_p), true negatives (T_n), false positives (F_p), and false negatives (F_n) - for each classifier. Five major metrics were calculated - overall accuracy (Acc), precision (P), recall (R), F1 score ($F1$), and the Matthews correlation coefficient (MCC) shown in Table 3.1.

Results

Binary Classification

The trained binary classifier, results seen in Table 3.2, achieved an overall accuracy (ACC) of 97.03%, F1 score of 97.05% and MCC of 0.9407 indicating the classifier was able to generalize on new images and accurately predict whether there was or was not a nilgai. The model validation accuracy improved by ~15% by going from the first to second stage of training. Recall (97.84%) was slightly higher than precision (96.28%) which is favorable for this unique problem. The occasional misclassified image of deer or cattle is preferred since these mistakes can be easily caught. A misclassified image of a nilgai, however is more detrimental to the overall goals of eradication efforts and is less likely to be caught since the pool of images in the unimportant "Not Nilgai" class is significantly larger.

Multiclass Classification

The multigroup classifiers achieved an overall accuracy of 84.77%. Group-wise test results and evaluation metrics found in Table 3.3 show that three of the most highly correlated classes - squirrel, skunk, and tortoise - were the most imbalanced with each having less than 20 images. Figure 3.4 shows a random sample of predictions made on test results. The three most common groups in the dataset – "Nilgai", "Deer", and "None" – were strongly correlated with MCC of 0.76, 0.79, and 0.80 respectively.

Discussion

We looked at how a small amount of hand-labeled camera trap images can be used to train a CNN to automatically detect wildlife. In the case of binary classification, evaluation results showed an accuracy of 97% . The limitations of training a multigroup classifier was explored. Results found that class imbalance played a role in skewing the accuracy of rare classes. Despite containing fewer than 50 images, the classification accuracies for rare classes like skunk, tortoise, and squirrel were high. Upon further inspection, the test images were found to be very similar to training images. For example, the tortoise's slow movement was enough to trigger camera sensor multiple times which resulted in many nearly identical images. Ultimately, because rare groups contained even fewer number of images in the test set, it was difficult to evaluate their accuracy. Addressing the class imbalance issue is an important factor in improving results and includes classifying capture events or exploring other sophisticated balancing techniques. One such technique is *emphasis sampling* (Norouzzadeh et al. 2018) where misclassified images are repeated, or emphasized during training, more so than correctly classified images. Alternatively, one could simply add images to rare classes from other camera trap datasets (e.g. Snapshot Serengeti or other online databases). However, this approach risks introducing too dissimilar images and class types. Lastly, adopting a trained model into an automatic camera trap classification workflow should be closely monitored by inspecting important and rare groups for anomalies or by testing on a subset of new images. An emphasis should be placed on inspecting groups with environments not initially used during training. New camera angles, species, or locations could pose challenges to accurate classifications.

Deep learning approaches have become a ubiquitous tool among major industries (Ahmed and Islam 2020). Training neural networks, however, is no small task. Moreover, maintaining a growing database of camera trap images develops an evolving demand for refined classification results. An important component of any data-intensive conservation project thus includes interdisciplinary collaborations that connect technologists with researchers, students, and field technicians. These collaborations help define real-world problems that in turn facilitate successful development and long-term application of these tools (Lamba et al. 2019).

Conclusion

This study showed how nature specific transfer learning has the potential to save enormous amounts of time and resources typically required to hand-label camera trap images. A trained classifier making predictions on 3,000 raw images saves roughly 12 personnel hours (Goolsby, pers. communication) that can then be transferred to other tasks. Automating this time-intensive process dramatically reduces the cost that can then be redirected to enable future studies of population dynamics in conservation ecology (Norouzzadeh et al. 2018). More importantly, results showed the possibility of open-sourced tools, datasets, and the developing global library of pre-trained models can be leveraged to implement state-of-the-art deep learning techniques on a small dataset of local camera trap images.

Tables and Figures

Table 3.1 Evaluation Metrics

Acc: Accuracy	$\frac{T_p + T_n}{T_p + T_n + F_p + F_n} \cdot 100$	Calculates the ratio of all correct predictions out of all instances.
P: Precision	$\frac{T_p}{T_p + F_p} \cdot 100$	Calculates the ratio of true positives to total test positives.
R: Recall	$\frac{T_p}{T_p + F_n} \cdot 100$	Calculates the ratio of true positives to all conditional positives.
F1 Score	$2 \cdot \frac{T_p}{T_p + F_p + F_n} \cdot 100$	Uses precision and recall calculating the harmonic mean that applies a harder penalty when one measure improves at the expense of another.
MCC: Matthews correlation coeff.	$\frac{T_p \cdot T_n - F_p \cdot F_n}{\sqrt{(T_p + F_p) \cdot (T_p + F_p) \cdot (T_p + F_p) \cdot (T_p + F_p)}}$	Measures the correlation between true and predicted results of the classifier using values between -1 and +1.

Table 3.2 Binary Model Testing Results

Metric	
Population	10,000
Condition positive – nilgai	5,000
Condition negative - not nilgai	5,000
Total predicted Positive - nilgai	5,081
Total test Negative - not nilgai	4,919
T_p: True Positive	4,892
T_n: True Negative	4,811
F_p: False Positive	189
F_n: False Negative	108
TPR: Recall (true pos recall)	97.84%
PPV: Precision (pos pred value)	96.28%
ACC: Accuracy	97.03%

F1 score	97.05%
MCC: Matthews correlation coefficient	**0.9407**

Table 3.3 Multigroup Model Testing Results

Class	# Imgs.	T_p	T_n	F_p	F_n	Acc.	Recall	Precision	F1	MCC
Armadillo	262	241	9717	21	21	91.985	91.985	99.580	91.985	0.918
Birds	856	781	9070	74	75	91.345	91.238	98.510	91.292	0.905
Cat	449	366	9508	43	83	89.487	81.514	98.740	85.315	0.848
Cattle	1325	1142	8589	86	183	92.997	86.189	97.310	89.463	0.880
Coyote	489	421	9444	67	68	86.270	86.094	98.650	86.182	0.855
Deer	867	743	8998	135	124	84.624	85.698	97.410	85.158	0.837
Dog	99	88	9900	1	11	98.876	88.889	99.880	93.617	0.937
Horse	12	12	9983	5	0	70.588	100	99.950	82.759	0.840
Humans	869	784	9101	30	85	96.314	90.219	98.850	93.167	0.926
Mouse	683	582	9277	40	101	93.569	85.212	98.590	89.195	0.886
Nilgai	805	700	9057	138	105	83.532	86.957	97.570	85.210	0.839
None	857	770	8984	159	87	82.885	89.848	97.540	86.226	0.850
Opossum	201	182	9759	40	19	81.982	90.547	99.410	86.052	0.859
Pig	788	713	9144	68	75	91.293	90.482	98.570	90.886	0.901
Rabbit	561	524	9367	72	37	87.919	93.405	98.910	90.579	0.900
Raccoon	584	535	9374	42	49	92.721	91.610	99.090	92.162	0.917
Rat	537	501	9384	79	36	86.379	93.296	98.850	89.705	0.892
Skunk	21	20	9979	0	1	100	95.238	99.990	97.561	0.976
Spider	19	17	9977	4	2	80.952	89.474	99.940	85.000	0.851
Tortoise	12	12	9987	1	0	92.308	100	99.990	96.000	0.961
Turkey	153	150	9827	20	3	88.235	98.039	99.770	92.879	0.929

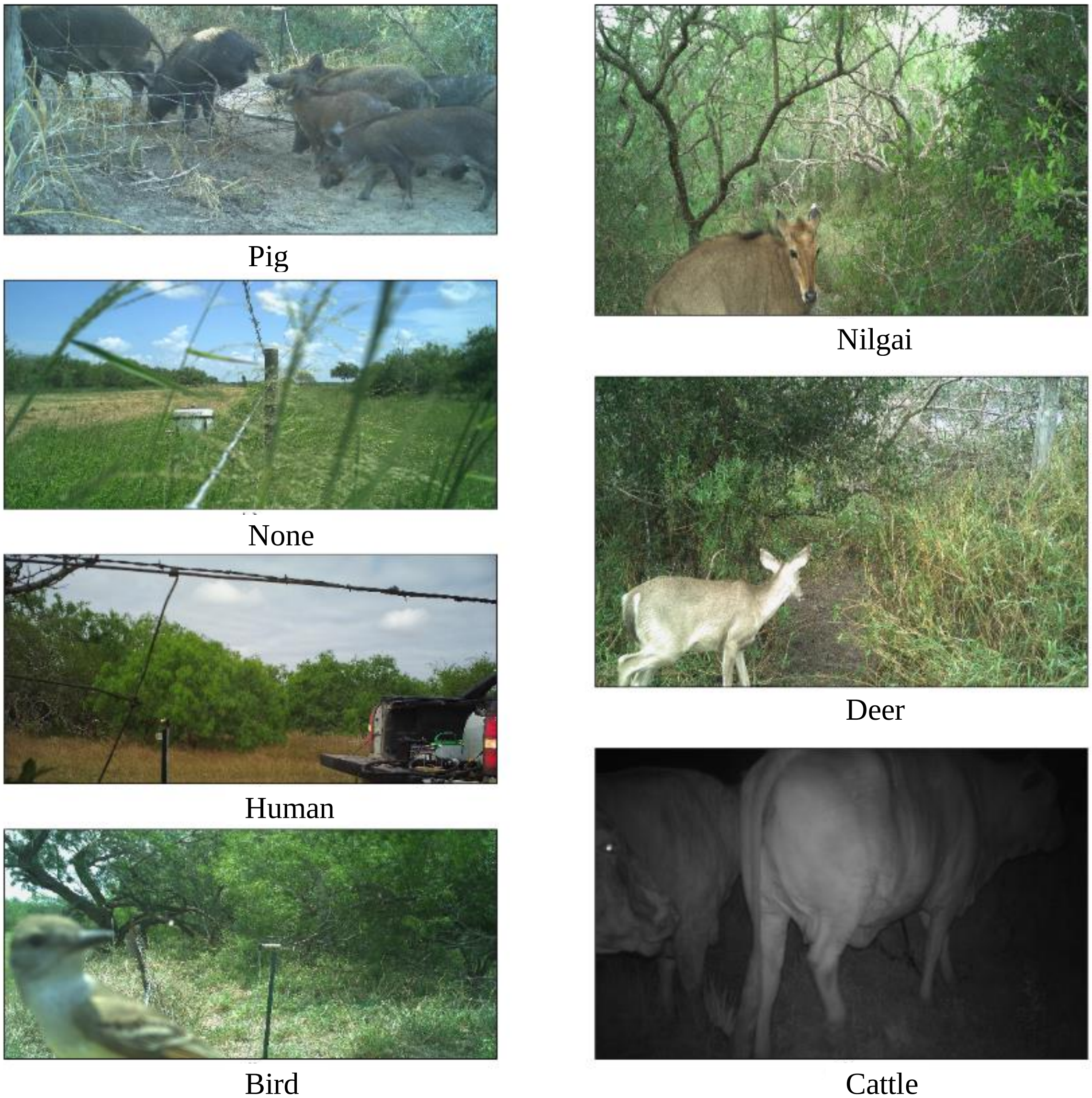


Figure 3.1 The Seven Most Common Animal Classes

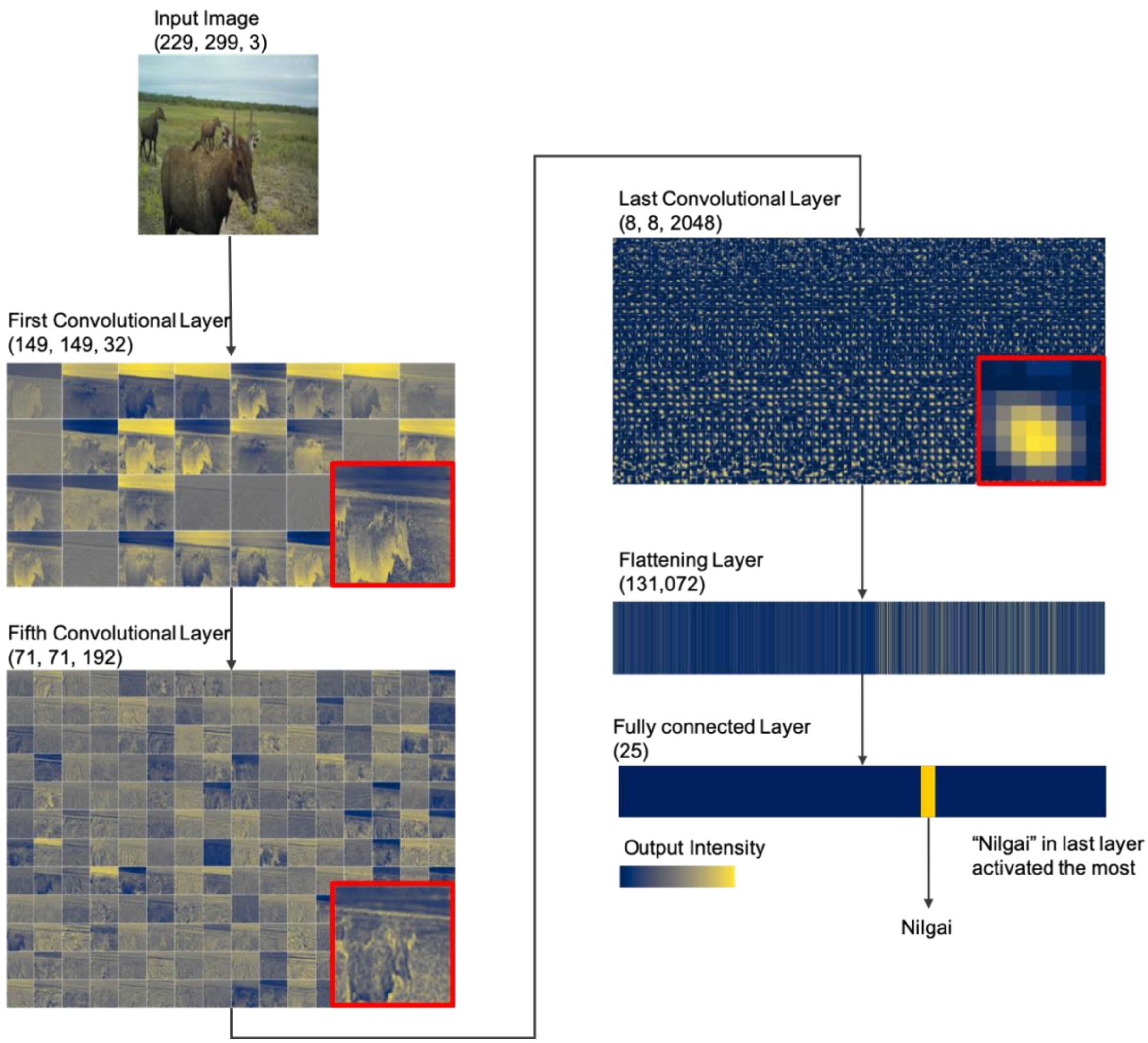


Figure 3.2 Inside A Convolutional Neural Network

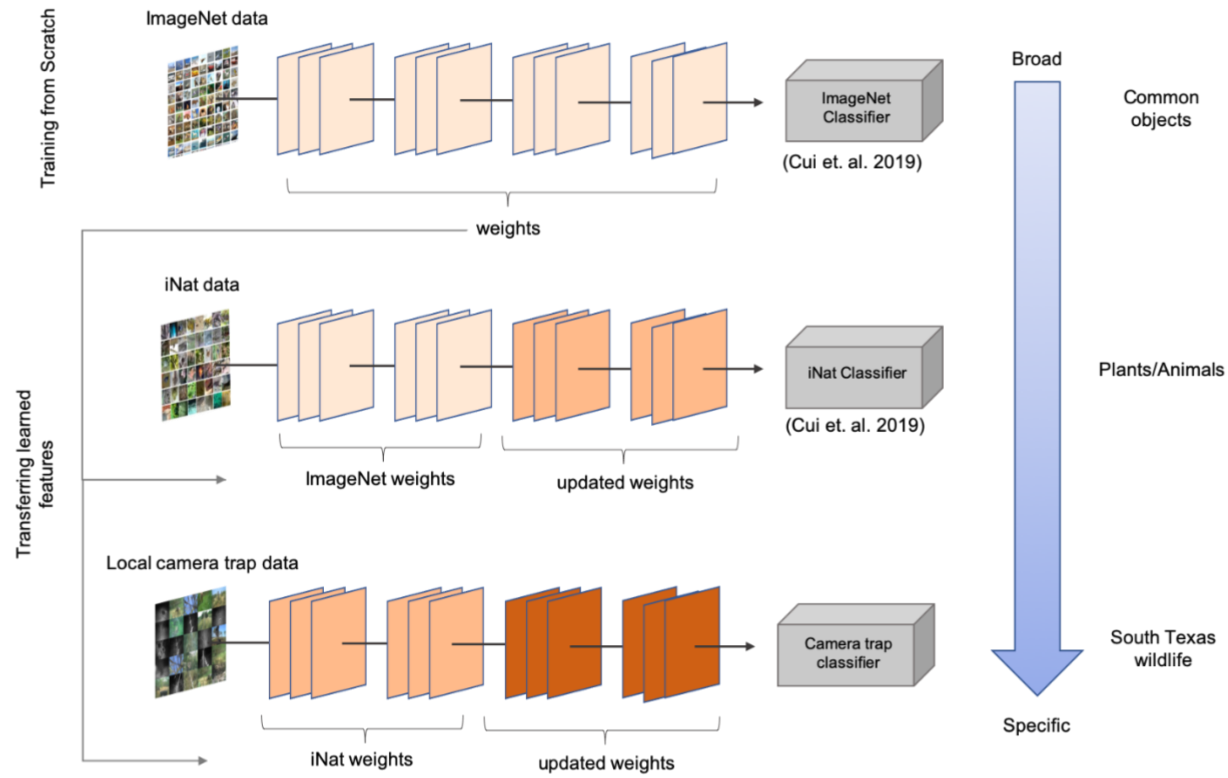


Figure 3.3 Nature Specific Transfer Learning

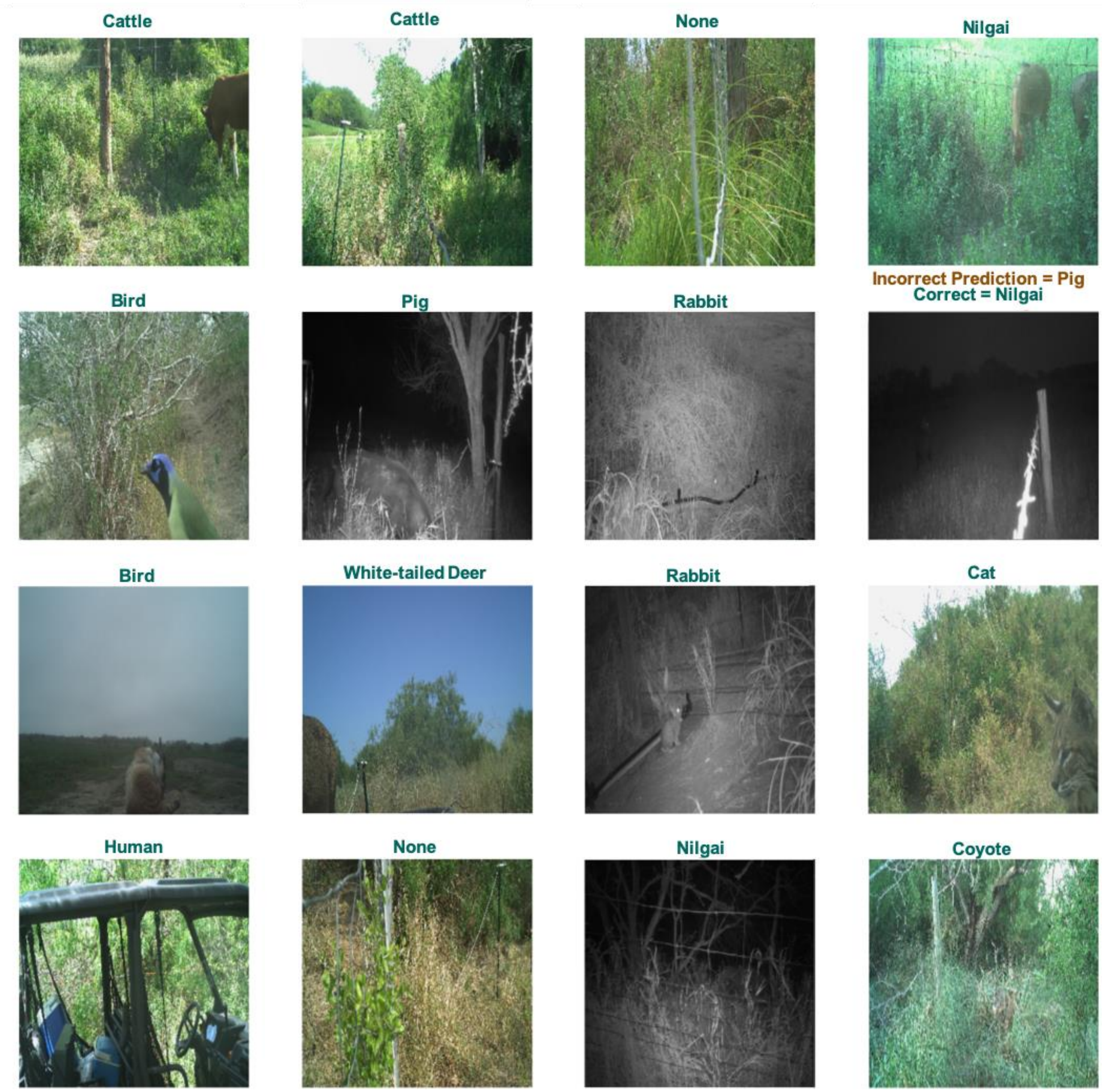


Figure 3.4 Model Predictions

CHAPTER IV

CONCLUSION, LESSONS LEARNED, AND FUTURE STUDIES

Conclusion

Proximal sensing are two important tools that can be used by researchers and conservation practitioners. These techniques extend the capabilities of researchers to gather and analyze large amount data that better inform decision-making. UAS-based proximal sensing was used to capture full-field plant data of 5.2 hectares of cover crops trials while proximal proximal sensing, or camera-trapping, was used to collect images that were used to train CNN that could automatically catalogue images.

Monitoring agroecological systems is a challenging task. Small sample sizes of traditional techniques drastically reduce the complexity of problems and fail to capture the nuance within complex systems. This study proved useful in establishing the potential of proximal sensing to provide insight into large-scale agroecosystems. Images, either taken proximally from a UAS or proximally by camera trap, were used to develop methods that reduce the need for burdensome data collection and analyses.

The goal was to provide examples of how proximal sensing can aid in the collection of data by researchers and conservation practitioners on the ground. The first example used UAS-based proximal sensing to capture the variability of canopy cover across large-scale cover crop trials. A UAS equipped with a multispectral sensor gathered images that to estimate canopy cover across ~5.2 hectares of on-farm cover crop trials and throughout the falls 2019 season. Images of each capture event were processed and combined to make a multiband orthomosaic. A normalized difference vegetation index was used to differentiate soil from vegetation and grid-wise samples were taken across the field. Canopy cover estimations for each treatment were averaged, analyzed, and compared across treatments and through time. While, canopy cover alone is insufficient to evaluate the efficacy of certain cover crops, it is one of many important agronomic plant metrics used to assess a cover crops benefit. Results showed that a mix dominated by radish and cowpea created the most canopy cover while sunnhemp treatments provide the least (except control treatments) which further bolstered visual assessments made on the ground. Most striking was the fact that sunnhemp treatments planted at 50.4 kilos. per hectare showed no difference in canopy cover compared to sunnhemp planted at 18 kilograms per hectare--more was not better in this case. Results also showed that for both mixes, canopy cover did not increase past 67 days after planting, while both sunnhemp treatments continued to increase beyond this point. While canopy cover alone is not enough to determine the efficacy of certain cover crops, it can be used with other important plant and environmental data to improve management strategies.

The second project provided an example of how open-sourced tools and shared models can be applied to address the common problem among wildlife monitoring – cataloging the many images that accumulate from camera trap platforms. More specifically, results showed how models pretrained on nature specific data and a small set of local camera trap images can be used to train a CNN that automatically catalogues images of wildlife. A CNN was trained on 110,000 images pulled from a local database containing 20 classes of species and one class labeled “None”. This approach was used to train two models, a multigroup classifier that identified 21 classes with an accuracy of 89% and a binary classifier able to discriminate images with animal of interest, “Nilgai”, and “Not Nilgai” with an accuracy of 97%.

The goal was to provide examples of how proximal sensing data could aid in data collection and analysis processes. Future work should consider integrating UAS-based proximal sensing data with deep learning. Potential exists in integrating UAS big agricultural data to train CNN and leverage the accumulated knowledge of pretrained models. This is especially true for addressing problems that involve counting plants, detecting weeds, and measuring surface temperature. Major obstacles, however, exists that limit the potential of deep learning techniques to be used in addressing these problems. For example, training CNN on images requires a large amount of computational resources and knowledge in computer vision, the discipline of using computers to perform human-level visual task and in image segmentation, the process of partitioning an image into multiple segments with the aim of simplifying its contents in a way that makes it easier to analyze. Though segmenting individual weed species from cash crops has been done and proven to be helpful in understanding management practices (citations), segmenting multiple species in a cover crop mix could provide meaningful information about weed suppressing abilities and perhaps additional selection criteria when investing in these conservation approaches

Proximal sensing and deep learning can be used as tool to investigate changes in local agricultural industries. For example, training a CNN on multitemporal satellite imagery of citrus orchards can help identify changes from the introduction of large-scale stakeholders on an industry traditionally dominated by small-scale farms. The collection and utilization of large agricultural data has untapped value in assessing the spatial and temporal impacts of conservation practices on wildlife and in agricultural systems. One of the key objectives of this work was to demonstrate how these technological advances can be employed in different settings. This work shows that proximal sensing data could be helpful for researchers and conservation practitioners in the identification of wildlife and assessment of agricultural management strategies.

Lessons Learned

Out of 22 flights, 4 were used for this research. Weather played a major role in negatively impacting the end mapping product. Even a small but dense cumulus cloud mid-flight can create a large blotch on the end orthomosaic product. Finding a day without clouds in the fall in south Texas is a challenging task along with scheduling flights. Other issues arose concerning the integration of sensor to drone. Flights were often canceled at the study site due to an inability to properly connect to GPS units or from poor WIFI connection between sensor, drone, and remote control tablet. An important lesson learned was to check firmware updates for the flight controller, batteries, and other associated equipment. In the end, it was particularly helpful to develop a system where we could easily remove the drone to update software every couple of months. Future users should plan to fly often with the expectation that a limited number of realized flights will occur.

A number of important mistakes were made. Initially, cover crops were to be further evaluated using crop height models where photogrammetry techniques can estimate the height of vegetation. This approach depends on accurate and precise location information that should be gathered by correcting for error using Continually Operating Reference System (CORS) data. Unfortunately, this process was not done correctly in time to gather data of the bare non-vegetated field required to perform the analysis. The second mistake occurred after the cover crops were terminated and the field was bare again. This time an uncalibrated inertial measurement unit, or IMU, located in the multispectral sensor and responsible for measuring orientation kept the drone from flying - a safety response put in place to keep from damaging the sensor, drone, or pilot.

Further, without a background in robotics or software development, the largest obstacle to overcome was a lack of time to learn and understand the many details that were needed to either operate a UAS or train a model. My experience with this project has given way to some concerns about the transferability and accessibility of these techniques. Without the resources and time to experiment it would be difficult to utilize these techniques in an efficient manner. Concerns about accessibility, however, are a testament to the increased need for institutions to invest in students and continue to provide them with the opportunities of time to develop their own base of knowledge.

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BIOGRAPHICAL SKETCH

Matthew D. Kutugata graduated from the University of Texas in Austin in 2012 with a B.A. in Geography. He spent 6 years working in parks, farms, and with non-profits learning about the challenges of producing food and managing land. He became interested in programming in 2017 after taking an online course in the Python programming language. He quickly realized the potential impacts simple code could have on creating efficient systems. His experience in conservation land management and computer programming motivated his interest to combine the two and apply them to sustainable agriculture. He joined the agroecology lab in 2018 and completed his M.S. in Agricultural, Environmental, and Sustainability Sciences in the summer of 2020. You can reach Matt at mattkutugata@gmail.com.