ABSTRACT

MANNING, JOSEPH DOUGLAS. Deployment of Unmanned Aerial Systems within Organizations. (Under the direction of Dr. Larry Silverberg).

This dissertation presents a framework for the process of deployment of unmanned aerial systems (UAS) in organizations through examining two case studies of drone deployment for wildlife applications in Africa's savannah. First, a feasibility study was conducted to test whether there may be a lowest altitude range for which the ungulates are not exceedingly disturbed and that over time the level of disturbance will reduce in the presence of UAVs. The results suggest strong correlations between flight altitude and response across the different ungulates and evidence that suggests rapid habituation to the UAVs. Next, a framework was developed for deployment of UAS in organizations. The development is based on previously described case studies and the theory of innovation. The process is described in six evolving steps encompassed by three stages. The first stage is development accomplished by merging knowledge bases, planning and conducting exercise, and reviewing findings. The second stage is modelling accomplished by building mathematical models relating key UAS and domain parameters. The final stage is implementation accomplished by documentation and execution. Three aspects of deployment were found to be of particular importance - system reliability, its evolutionary nature, and the UAS/domain interface.

Deployment of Unmanned Aerial Systems within Organizations

by
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DEDICATION

I dedicate this dissertation to two people that have always and will always mean so much to me. Both of whom were lifelong learners and education was a foundational piece of their lives. Their hard work knew no bounds and influenced everyone around them. Foremost, to my late father, Charles “Rocky” Manning, III, for his continued dedication and unwavering support for me throughout my life. Thanks for sticking with me.

And second, but just as important, I would also like to dedicate this to my paternal grandfather, Charles “Chuck” Manning, Jr. The person that convinced me to pursue a doctoral degree. A journey that felt so unique and put me in positions that I never would have dreamed I had the strength to overcome. I’m sure you always knew I could.

BIOGRAPHY

Joseph Manning was born and raised in Raleigh, North Carolina. He attended North Carolina State University receiving his B.S. in Mechanical Engineering in 2013 graduating Summa Cum Laude, and his M.S. in Mechanical Engineering in 2015. He will complete his PhD in Mechanical Engineering at North Carolina State University in 2021.

Before attending engineering school, he obtained a job as a technician at Accident Reconstruction Analysis, Inc. where he first gained his desire to attend engineering school through the ability to work on an extensive list of different engineering problems. During his graduate studies at NCSU he was asked to join the Namibia Wildlife Aerial Observatory project that was developed by Dr. Silverberg. Throughout his time with the program, he helped develop novel aerial systems for wildlife applications and led groups of students through the savannah gathering data.

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CHAPTER 1

Introduction

This dissertation presents a framework for the process of deployment of unmanned aerial vehicles (UAV) in organizations, drawing from general methodologies for innovation with a non-regulatory focus. The body of knowledge contained in both the unmanned aerial systems (UAS) and business domains fail to address a methodology that highlight advantages or complications within a deployment process for when a business decides to deploy a novel UAS. This problem has been illuminated countless times as UAS have proven to be a useful tool in a myriad of applications between inspection, mapping, monitoring, and delivery through research in engineering (e.g., Chabot & Bird, 2015; Chen, et al., 2019; Gonzalez, et al., 2016; Beck, et al., 2020); Yet, more often than not its recognized by those who follow deployment of drones in organization many fail despite their highly attractive promise. This research aimed to answer that complex engineering and business problem by examining two different case studies as a strategy; the objective in the deployment in the first case study was aerial counting of high-valued animal species in the African savanna and the objective in the second was aerial surveillance for anti-poaching of high-valued animal species in the African savanna. The research assumed that general methodologies would become evident through rigorous examination of the case studies accompanied with an assessment of current literature on new product development and implementation after the deployment of both systems. This process would begin with feasibility studies to validate the use of UAVs in specific operations. This is demonstrated in the second chapter.

The second chapter presents an example of a viability study done for the purpose of the aforementioned studies. In the preliminary stages after meeting with numerous wildlife experts, the question arose as to the viability of UAVs within wildlife domains due to the possibility of excessive disturbance of the wildlife. This was significant for both studies as biodiversity surveys monitor wildlife and antipoaching efforts are conducted in areas of protected wildlife. Therefore, this chapter examines whether there may be a lowest altitude range for which the ungulates are not exceedingly disturbed and that over time the level of disturbance will reduce, dictating a practically achievable level of discernibility in flight observation. This was achieved by testing the hypothesis that "the likelihood that the species will react and level at which they do to the unmanned aerial vehicle (UAV) is related to the altitude, number of passes, sound intensity, type of drone, takeoff distance, apparent size, and species."

This question strongly influences the future viability of the UAV in the study and protection of the ungulates in Africa's savanna. The ungulates were unhabituated to the UAVs and the study was conducted in the presence of stress-inducing events that occur naturally in the environment. The results suggest strong correlations between flight altitude and response across the different ungulates and evidence that suggests rapid habituation to the UAVs. As seen with the reference vehicle, Phantom 3, there was a less than 7.5% chance of inducing a movement response at 55 meters. Additionally, after the average number of passes (4.5) at 55 meters, the predicted probability of response reduces by approximately 80% of its initial value. After validating the viability of UAVs for use in these specific wildlife applications, further studies were carried out for use in both wildlife counting and antipoaching to examine development and deployment of these systems.

The third chapter develops a framework for deploying UAS into organizations based on the case studies and the theory of innovation (e.g., Birken et al., 2017; Mirvis et al., 1991). These studies were carried out by the author over the course of a three-year period in the Fall of each year from 2017 to 2019 with three different groups of students. The studies were developed and later analyzed while working closely with both a group doing wildlife abundance surveys and antipoaching toward defining how they could practically fit within their organizations to see sustainment of use. This practicality emerges in a variety of manners from vehicle capabilities and user-friendliness to human resource requirements that would need to come from the organization to operate systems of this nature. The process is described in six evolving steps encompassed by three stages. The first stage is development accomplished by merging knowledge bases, planning and conducting exercise, and reviewing findings. The second stage is modelling accomplished by building mathematical models relating key UAS and domain parameters. The final stage is implementation accomplished by documentation and execution.

The fourth and final chapter is a summary and conclusion to the findings emphasizing the three aspects of deployment of particular importance. These were found to be – system reliability, its evolutionary nature, and the UAS/domain interface.

An in-depth review of the literature is given in the introduction of each subsequent chapter.

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CHAPTER 2

Ungulate Responses and Habituation to Unmanned Aerial Vehicles in Africa's Savanna

INTRODUCTION

The highly valued ungulates in Africa's savanna, making up more than 25% of its landscape, might be effectively monitored by unmanned aerial vehicles (UAV) [1]. The question of this article concerns the extent to which ungulate responses might allow aerial wildlife monitoring (AWM) by UAVs. The hypothesis is that ungulate-UAV interaction depends strongly on flight altitude, that flying too low could excessively disturb them, and that there may be a lowest altitude range for which the ungulates are not exceedingly disturbed (putting aside for the moment how exceedingly disturbed is quantified) – dictating some achievable level of discernibility in flight observation. This question is valuable because it strongly influences the future viability of the UAV in the study and protection of the ungulates in Africa's savanna.

Several articles have already examined the effect of UAV altitude on non-ungulate response (data containing 5 to 100 trials). Biologists found that bears have an increased heart rate when the UAV flies 200 meters from the bear, 20 meters above it [2]. Scientists surveyed elephants in Burkina Faso, flying at altitudes of 100 meters and 300 meters over 10 km transects [3]. Researchers found that the influence of the UAV on the penguin is significant at an altitude of twenty meters [4].

Note that the AWM engineer or designer, when laying out a system of UAVs to monitor a field, would begin by selecting a flight altitude after which vehicles and a communication network would be selected, and in more advanced systems sophisticated data patching methods and graphical interfaces employed [1]. Other preparations, too, would be necessary depending on the application. Indeed, the large number of reported studies and methods preparing for AWM strongly suggests that the potential AWM applications are plentiful. Considering just a few of the articles, studies have focused on the cost savings [5], the management role [1], and more applied work on wildlife tracking [6], counting methods [7-9], and anti-poaching [10].

In general, the level of danger that an ungulate perceives strongly influences its response. The perceived danger that a UAV poses could come from the ungulate-UAV distance, sensed by an auditory signal, or it could come from secondarily observing the responses of neighboring species who have already responded to the UAV. In Africa's savanna, one finds many ungulates in mixed herds so one could expect neighboring herds to trigger a response. The usual source of the danger to the ungulate comes from the ground, not the air. Therefore, the level of response could be moderate or low depending on flight altitude, while differing from species to species. One also expects the responses to depend strongly on the environment. The time of day (before or after eating), the proximity of nearby animals posing a danger, and the passing by of vehicles or other stress inducing events would be expected to influence the responses.

This article outlines one of the first longitudinal studies of animal response by a UAV. These operations were conducted in a harsh environment, under high altitude and high heat conditions, where maintaining regular operations was difficult. Locating animals to perform flights was

difficult and time consuming and often required considerable hiking for even a limited number of passes and in some circumstances no passes due to failed preflight checks after problems in the field. Even under these unfavorable conditions, the team was able to persevere and acquire 397 passes (trials) over 99 flights.

In this article we examine *how* these ungulates located in the Savannah respond to UAV presence. Specifically, we determine how representing the effects of UAV presence with independent variables that are either continuous, ordinal categorical or qualitative nominal classes might impact our understanding of what drives species reaction. We hypothesized that: (i) altitude (or proximity) is a driving factor and that (ii) the animals will undergo habituation because these ungulates are not normally predated by an aerial foe. To test our hypotheses, we focus on monitoring the wildlife under a variety of conditions in their natural environment through a large data set to see if these factors emerge.

The method section describes the study site, the wildlife species monitored, the data collection process, the aerial vehicles, and the data collected. The results section gives the ungulate responses, the occurrences of responses and discusses the data and secondary factors. Finally, the article summarizes the results and draws conclusions.

MATERIALS AND METHODS

Study Area: The study was conducted at a wildlife sanctuary (N/a'an ku se) located about 40 km east of Windhoek, Namibia's capital city, over a ten-week period in 2017 from September to November. The land is 25 km^2, located on Namibia's central plateau, and its elevation is 1600 to

1800 meters. From September to November, the average temperature is 20 to 23 C, and the average rainfall is 10 mm in September, 10 mm in October, and 30 mm in November. The land is a semi-closed eco-system surrounded by an 8-foot game fence that includes free ranging leopards and cheetah and the species are unhabituated to UAVs. Fig. 1 is a map of the test site. The study species included a group of ungulates commonly found in arid savannah eco-systems throughout Africa: Oryx (*Oryx gazella*), Eland (*Taurotragus oryx*), Giraffe (***camelopardalis***), Springbok (*Antidorcas marsupialis*), Hartebeest (*Alcelaphus buselaphus*), Plains Zebra (*Equus quagga*), and Kudu (*Tragelaphus strepsiceros*).

A field unit of 12 students collected data over a 10-week period (See the acknowledgement section). The field unit formed data collecting sub-units, each consisting of four personnel: (1) a pilot, (2) a primary observer, (3) a ground camera operator, and (4) a data recorder. The pilot was responsible for flying the UAV. When flying in RC mode, the pilot was also responsible for operating the flight camera and maintaining visual contact with the study species from the air. The primary observer was responsible for observing the species and maintaining visual contact with the ground station. The primary observer worked next to the data recorder and relayed all of his wildlife response observations throughout the flight to the recorder. The ground camera operator was responsible for photographing/video recording the responses. The data recorder was responsible for annotating information relayed from the primary animal observer on a flight-data collection sheet.

Experimental Design: The purpose of this study was to assess ungulate responses to UAVs flying at different altitudes in Africa's arid savanna. Several considerations were vital when

setting up the study. First, the protection of ungulate wildlife from human interaction favors human interactions that are sufficiently unobtrusive such that it requires no or a minimal level of habituation. Furthermore, ungulate habituation, when none of the conditioning is negative, would only tend to decrease the altitude that an ungulate tolerates. Therefore, for the purposes of this study, it was reasonable to focus on unhabituated ungulates, recognizing how the results of this study would extend to habituated ungulates and assess whether habituation is possible. Secondly, in order for the results to apply to the natural habitat of the savanna, it was also important to perform the study in the mixed herd environment in the presence of its naturally occurring stress inducing events. The variable conditions of the natural environment introduce noise into the study that increases the difficulty to discern the effect of altitude on the response data. However, it can also determine whether or not UAV altitude is a dominant factor against the other factors, as hypothesized.

The ungulate response was gathered at four levels. The levels were designated by the following: No Response (no discernable movement), Alert (eye/head movement and/or turning of the upper body), Relocation (moving out of the way of the UAV but still in sight), and Flee (significant movement from UAV location). Due to the very low number of flee responses and the similarity of the movement aspect, the two location movement responses (Relocation and Flee) were combined into one category (Movement), which was categorized as relocation away from the UAV. Therefore, the data were analyzed by three categories (No Response, Alert, Movement).

The suite of UAVs consisted of the DJI Phantom 3 (the reference vehicle), DJI Mavic Pro, Custom X8 (Also referred to as an Octocopter), and Sky Eye. Table 1 shows the tested noise levels of the different UAVs with their baseline equivalent altitudes.

Table 1: UAV Noise Levels.

UAV type	Frame size (mm)	Weight (g)	Noise level (dBA)	Altitude (m)
Phantom 3	350	1280	60.24	50
			Reference altitude	50
Mavic Pro	335	734	45.7	50
			Phantom equivalent altitude	266.7
Sky Eye	2000	2000	52.5	50
			Phantom equivalent altitude	121.9
Custom X8	650	4400	65.0	50
			Phantom equivalent altitude	28.9

As shown, the loudest to quietest vehicles were the Custom X8, Phantom 3, Sky Eye and Mavic Pro. Noise disturbance is not only influenced by the noise which can be qualified by sound intensity (dB) and frequency (Hz), but also by its duration and pattern. The age and physiological state of the animal at the time of exposure, the exposure history of the animal, and the predictability of the acoustic stimulus can also play a role [11]. The effect of altitude on animal response was studied in the presence of all of these naturally occurring factors.

The design of the experiment began with determining a range of flight altitudes. The range of flight altitudes was determined through 23 preliminary flights, flying at altitudes from 20 meters to 100 meters in 10-meter increments. We determined that 15 meters was a suitable lower bound because of safety concerns and that 55 meters was a suitable upper bound because negative response had already significantly dropped off by that altitude. The data collection process began every morning with locating animal herds and setting up a field unit nearby. Local personnel understood the best locations to set up field units and launch the UAVs. As shown in Fig. 1, the

launch points were located in the low-lying, open areas along the roads. The data collecting personnel hiked or travelled by ground vehicle to those launch points.

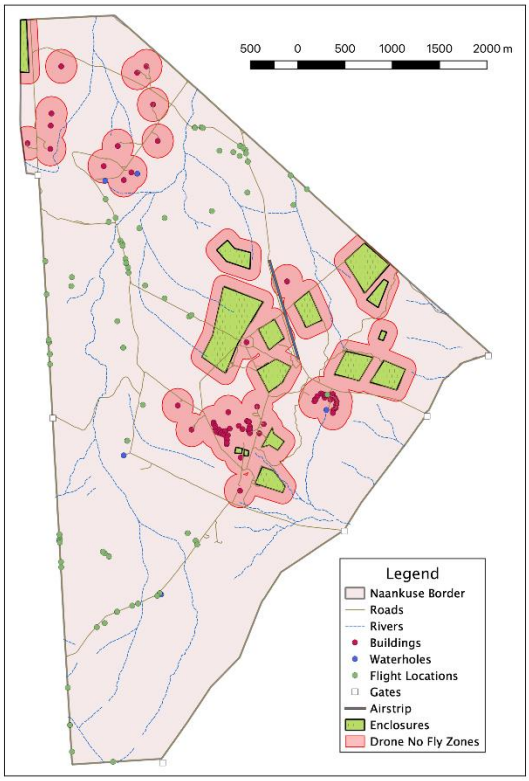

Figure 1: N/a'an ku sê Map and Flight Locations.

The horizontal distances between the animals and the field unit points varied widely – between 50 and 600 meters (measured in 25 m increments). The units logged this data to determine its effect on the responses, if any. The total data set consisted of 397 passes (trials) over 98 flights, however, the analyzed dataset not including preliminary flights was 346 passes over 76 flights that ranged in altitude from 15 to 55 meters. Each pass began with taking off from a launch point, flying about 200 m away from a spotted animal group, changing altitude as appropriate, and then flying 400 m, passing over the animal group. The UAV was flown over the animal or herd at 10 m/s. The next pass was flown at another randomly selected altitude. If a movement response was invoked (relocation or flee), the drone would wait at a distance while the animals

would settle back to a sedentary behavior. Passes were continued until battery levels were too low to continue or the animals were no longer within sight. Table 2 shows the procedure that each of the members of the field unit followed.

Table 2: Field Unit Procedures.

Pilot	Pre-flight checklist, flight, post-flight checklist, reports damage or concerns at end of day
Camera operator	Pre-flight and post-flight checklist for camera and gimbal, ensure the data are downloaded, sd card cleared at end of day, assists pilot with DJI drones.
Animal observer	Observes surrounding field prior to takeoff for safety, observes animal responses during flight, decides whether to continue or end mission based on animal behavior.
General observer	Ensures all of the roles are being properly executed, ensures that no wildlife is encroaching upon during the flights, assists the data collector in obtaining data during the flights when several tasks are being performed simultaneously.
Data entry	Enters all of the pre, during, and post flight data

Statistical Analysis: An ordinal logistical regression was chosen due to the ordered nature of the response between No Response, Alert, and Movement. These models were developed using R 4.0.5 (R Development Core Team 2021). Several model generating techniques were used from three packages, the polr function from the MASS package [12], vglm from the VGAM package [13], and the cumulative link model (clm) from the ordinal package [14]. These different models were useful in testing variable significance, developing the best fit model, testing the proportional odds assumption, and lastly fitting partial proportional odds models for variables that do not conform to the proportional odds assumption.

The first model was started by using the polr function, which comes from proportional odds logistical regression, in the MASS package (the proportional odds assumption will be tested later

in this analysis). Considering the large number of variables, the final models' variables were chosen using the Akaike information criterion (AIC). The AIC is an estimator of the relative quality of a model for a given data set by dealing with the tradeoff between goodness of fit and simplicity. The variables were first tested for independence before entering the model using the chi-squared test for independence. The best model was chosen by minimizing AIC to an extent and in close situations allowing the discretion of the researchers. Several iterations using the step function were run in forward, backward, and both direction configuration to confirm the best fitting model. An initial model containing all variables was fitted and run with an analysis of variance (ANOVA) type II test for significance of variables. This model was compared to the best fitting model to compare variable contributions. The variables that were left out were found to not have meaningful influence or significance. The final model was then chosen after analyzing that there were sufficient data to create a good fitting model given the current data set. Furthermore, the model was then tested to meet the proportional odds assumption and ensured that the model was an accurate representation of the data through various methods detailed in the results.

RESULTS

Data: The data set used in analysis did not include preliminary flights for testing and was 346 passes over 76 flights. The data consisted of species reactions (No Response, Alert, and Movement). Of these reactions, 164 (47.4%) were No Response, 115 (33.2%) were Alert, and 67 (19.4%) were Movement. The research hypothesis posed to the data was that "the likelihood that the species will react and level at which they do to the UAV is related to the altitude, number of passes, sound intensity, type of drone, takeoff distance, and species." Thus, the outcome variable,

Response, was the herds reaction to the drone after a pass taken overhead. The predictors were Altitude (a continuous variable using 15, 25, 35, 45, and 55 meters), Pass (the pass number over the herd during a given flight), Drone (Mavic, Phantom 3, Custom X8, Sky Eye), Sound Intensity (dB level that would have been experienced by animal herd estimated using altitude at pass an noise characteristic of vehicle), takeoff distance (herd distance from ground crew at takeoff measuring in meters), field of view (FOV, an apparent size seen by the animal based on the longest dimension on the drone), as well as each animal species with sufficient samples which were Oryx, Giraffe, Springbok, and Zebra in both single species and mixed group.

Species Reactions: The relative abundance of the different species varies from site to site and by season. Table 3 shows the populations of the monitored species at the test site. In some cases, single specie herds were observed while in other cases there were mixed herds.

Table 3: Number of passes (% of total passes).

Species	Single Species	Mixed Herd
Oryx	50 (14.45%)	120 (34.68%)
Giraffe	46 (13.29%)	14 (4.05%)
Springbok	46 (13.29%)	58 (16.76%)
Zebra	27 (7.80%)	87 (25.14%)
Other	39 (11.27%)	49 (14.16%)

As previously stated, the data were broken up by distinguishing between a single species encounter and a mixed herd encounter. Eland, Hartebeest, Impala, and Waterbuck were also found on the property; however, they were not passes over in enough flights to include in the species analysis. Therefore, the species predictors used were Oryx Single, Zebra Single,

Springbok Single, Giraffe Single, Oryx Mixed, Zebra Mixed, Springbok Mixed, and Giraffe Mixed.

Ordinal Regression Analysis: A 13-predictor ordinal logistical regression was fitted to the data to test the hypothesis relationship regarding the likelihood that a species will react based on the flight altitude, number of passes, sound intensity, type of drone, takeoff distance, FOV, and species. The Akaike Information Criterion (AIC) was used to find the best fitting model. This was done by eliminating predictors to minimize the models AIC score. This process was done in a backwards (starting with all of the predictors and eliminating), forward (Starting with no predictors and adding), and both directions (starting with a number of predictors and adding and eliminating based on AIC score) to find the best fitting model. Two models were found with similar AIC, both with the same predictors except one contained altitude and the other sound intensity. Interestingly, the sound intensity predictor was calculated from the altitude but did not show any correlation when tested. This was likely due to the large difference in the level of sound produced by the different drones.

The parallel lines test was done to test proportional odds assumption by comparing it to a general model (a saturated multinominal logistical regression). The comparison was done between the general model and using the Chi-Squared test to the multinomial logistical regression using the multinom() function from the nnet package [12]. The test showed the general model gives a significantly better fit ($p<0.05$) thereby inferring that the proportional odds assumption was not valid. However, the test of the proportional odds assumption has been described as anti-conservative, that it nearly always results in the rejection of the proportional odds assumption

particularly when the number of explanatory variables is large [15], the sample size is large, or there is a continuous explanatory variable [16]. The model was developed to counter this and was built in the ordinal package with the clm() function and tested the significance of the proportional odds assumption in using the nominal() function. The variables Drone and ZebraMixed were significant in the test indicating that the proportional odds assumption was broken. The Odds Ratios were viewed in the different model configurations to see if the estimators truly were different, and it was deemed that both Drone and ZebraMixed did not meet the proportional odds assumption.

The models were then developed as partial proportional odds models relaxing the proportional odds assumption for ZebraMixed and Drone. Finally, the model was tested again against the more general model and the general model was not found to be a significantly ($p<0.05$) better fit. The following table is the summary of the model. Evaluation of the models were done by taking an overall model evaluation, statistical tests of the individual predictors, goodness of fit statistics, and validation of predicted probabilities [17].

Models without interaction effects:

Model 1: *Response ~ Altitude + Pass + Drone + GiraffeSingle + ZebraMixed*

Model 2: *Response ~ dB + Pass + Drone + GiraffeSingle + ZebraMixed*

Table 4: Model 1 and 2 Summaries.

	Model 1			Model 2		
Predictors	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
(Intercept) * 1	17.71	7.56 – 41.52	**<0.001**	0.00	0.00 – 0.00	**<0.001**
(Intercept) * 2	1.46	0.64 – 3.32	0.372	0.00	0.00 – 0.00	**<0.001**
Altitude	0.94	0.92 – 0.96	**<0.001**			
Pass	0.81	0.72 – 0.90	**<0.001**	0.80	0.72 – 0.90	**<0.001**
Drone [Mavic] * 1	0.38	0.22 – 0.69	**0.001**	9.01	3.33 – 24.38	**<0.001**
Drone [Mavic] * 2	1.02	0.50 – 2.06	0.960	24.12	7.84 – 74.21	**<0.001**
Drone [Sky Eye] * 1	0.66	0.25 – 1.75	0.405	3.77	1.30 – 10.89	**0.014**
Drone [Sky Eye] * 2	1.15	0.33 – 4.04	0.822	6.69	1.73 – 25.87	**0.006**
Drone [Octo Copter] * 1	8.83	2.82 – 27.65	**<0.001**	3.13	0.99 – 9.88	0.051
Drone [Octo Copter] * 2	7.09	2.88 – 17.45	**<0.001**	2.61	1.06 – 6.45	**0.038**
GiraffeS [TRUE]	3.05	1.58 – 5.87	**0.001**	3.02	1.57 – 5.81	**0.001**
ZebraM [TRUE] * 1	2.07	1.12 – 3.80	**0.020**	2.02	1.10 – 3.70	**0.024**
ZebraM [TRUE] * 2	4.60	2.26 – 9.36	**<0.001**	4.46	2.18 – 9.12	**<0.001**
dB				1.24	1.17 – 1.32	**<0.001**
Observations	346			346		

Overall model evaluation: The overall model evaluation was done by comparing the model to an intercept only model (called the null model). Consequently, the significant chi-squared statistic (LR stat. = 102.23, Pr(Chi) =0) for model 1 and (LR stat. = 103.18, Pr(Chi) =0) for model 2 indicates the models containing predictors give a significant improvement over the baseline intercept-only model.

Statistical tests of individual predictors: The statistical significance of individual regression coefficients (i.e., betas) is tested using the Wald chi-squared statistic (Table 4). According to Table 4, Pass, Drone, Giraffe Single, and Zebra Mixed were significant predictors in both models as well as altitude in model 1 and dB in model 2 in the response to UAVs flying overhead of the

herds ($p<0.05$) and even accounting for the Bonferroni correction of Drone ($p<0.0083$) and ZebraMixed ($p<0.025$).

Table 5: Evaluation of Models using ANOVA Type II.

	Model 1				Model 2		
	Df	X^2	Pr(>X^2)		Df	X^2	Pr(>X^2)
Altitude	1	49.388	0.000	dB	1	51.143	0.000
Pass	1	14.527	0.000	Pass	1	15.341	0.000
Drone	6	41.108	0.000	Drone	6	38.670	0.000
GiraffeSingle	1	11.086	0.000	GiraffeSingle	1	10.981	0.001
ZebraMixed	2	17.759	0.000	ZebraMixed	2	16.846	0.000

Goodness-of-fit statistics: Goodness-of-fit statistics assess the fit of logistical model against actual outcomes. Three inferential goodness-of-fit tests were performed on the model: the Lipsitz goodness of fit test, the Pulkstenis-Robinson chi-squared test, and Pulkstenis-Robinson deviance test. Table 5 below shows the results of the tests. The Lipsitz test yielded a (model 1 = X^2 (df=9) of 7.6884, model2 = X^2 (df=9) of 11.965) and was insignificant ($p>0.05$), suggesting the models fit well to the data confirming the null hypothesis. Similar findings were concluded with the PR Chi-Squared test and the PR deviance test both yielding significant values ($p>0.05$) and confirming the null hypothesis that the model is a good fit to the data. Using both the PR test and Lipsitz test helps fully grasp the goodness of fit as PR tests work best when the lack of fit is associated with categorical variables, whereas the Lipsitz test works best when continuous covariates drive the lack of fit [18, 19].

Table 6: Goodness-of-fit Tests.

	Model 1			Model 2		
	X^2	df	p-value	X^2	df	p-value
Lipsitz	7.6884	9	0.566	11.965	9	0.215
Pulkstenis-Robinson X^2	6.401	12	0.895	6.548	12	0.891
Pulkstenis-Robinson deviance	7.256	12	0.840	7.416	12	0.829

Validation of predicted probabilities: The resultant predicted probabilities were then compared with the actual outcome to determine if high probabilities are indeed associated with events and low probabilities with non-events. The degree to which predicted probabilities agree with actual outcomes is expressed in the classification table below. The overall correct prediction was 60.1% for model 1 and 59.8% for model 2, a sizable improvement over the chance level (33.3%). In the opinion of Hosmer and Lemeshow (2000, p. 160), "the classification table is most appropriate when classification is a stated goal of the analysis; otherwise, it should only supplement more rigorous methods of assessment of fit." It was determined that based on the classification table and the goodness-of fit models that the data were properly fit to the model.

Table 7: Classification Table.

Observed	Model 1 Predicted				Model 2 Predicted			
	No Response	Alert	Movement	% Correct	No Response	Alert	Movement	% Correct
No Response	122	33	9	74.4	125	31	8	76.2
Alert	44	64	7	55.7	48	59	8	51.3
Movement	19	23	25	37.3	22	22	23	34.3
% Correct	65.9	53.3	61.0	60.1	64.1	52.7	59.0	59.8

Interaction effects were added based on the underlying main effects. For both models, the interaction effects between Altitude or dB (model 1 or model 2 respectively), Pass, and Drone were tested as well as the ZebraMixed with other mixed group species. Based on this analysis significant interaction effects were found in model 1 between Altitude and Pass as well as ZebraMixed and OryxMixed and similarly with model 2 between sound intensity and Pass and ZebraMixed and OryxMixed. There was significance found between Drone and (Altitude and sound intensity) but given the low number of samples with the Sky Eye and Custom X8, the model seemed to be saturated with some of the limited amounts of data. Similar to the initial

model evaluation the models containing interaction effects had an overall evaluation, statistical tests for individual predictors, goodness-of-fit tests, and validation of the predicted probabilities.

Models containing interaction effects:

Model 3: *Response ~ Altitude + Pass + Drone + GiraffeSingle + ZebraMixed*OryxMixed + Altitude:Pass*

Model 4: *Response ~ dB + Pass + Drone + GiraffeSingle + ZebraMixed*OryxMixed + dB:Pass*

Table 8: Model 3 and 4 Summaries.

	Model 3			Model 4		
Predictors	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
(Intercept) * 1	3.72	1.10 – 12.54	**0.034**	0.00	0.00 – 0.00	**<0.001**
(Intercept) * 2	0.28	0.08 – 0.98	**0.046**	0.00	0.00 – 0.00	**<0.001**
Altitude	0.98	0.95 – 1.02	0.330			
Pass	1.24	0.94 – 1.65	0.130	0.29	0.12 – 0.73	**0.008**
Drone [Mavic] * 1	0.33	0.18 – 0.62	**<0.001**	8.94	3.22 – 24.85	**<0.001**
Drone [Mavic] * 2	0.98	0.48 – 2.01	0.954	25.95	8.18 – 82.33	**<0.001**
Drone [Sky Eye] * 1	0.60	0.22 – 1.66	0.325	3.49	1.14 – 10.64	**0.028**
Drone [Sky Eye] * 2	1.15	0.32 – 4.22	0.830	6.52	1.61 – 26.40	**0.009**
Drone [Octo Copter] * 1	9.91	3.07 – 32.02	**<0.001**	3.68	1.15 – 11.81	**0.028**
Drone [Octo Copter] * 2	8.28	3.28 – 20.94	**<0.001**	3.23	1.27 – 8.23	**0.014**
GiraffeS [TRUE]	3.62	1.80 – 7.27	**<0.001**	3.58	1.80 – 7.11	**<0.001**
ZebraM [TRUE] * 1	11.72	3.13 – 43.88	**<0.001**	11.42	3.07 – 42.46	**<0.001**
ZebraM [TRUE] * 2	24.03	6.39 – 90.29	**<0.001**	23.18	6.22 – 86.39	**<0.001**
OryxM [TRUE]	1.68	0.79 – 3.58	0.177	1.77	0.83 – 3.75	0.137
ZebraM [TRUE] * OryxM [TRUE]	0.10	0.02 – 0.44	**0.002**	0.10	0.02 – 0.45	**0.003**
Altitude * Pass	0.99	0.98 – 0.99	**0.001**			
dB				1.19	1.10 – 1.28	**<0.001**
dB * Pass				1.02	1.00 – 1.03	**0.029**
Observations	346			346		

Overall model evaluation: The significant chi-squared statistic (LR stat. = 122.28, $Pr(X^2)$ =0) for model 3 and (LR stat. = 118.13, $Pr(X^2)$ =0) for model 4 indicates the models containing predictors give a significant improvement over the baseline intercept-only model. This was expected since the models were only adding interaction effects.

Statistical tests of individual predictors: The statistical significance of individual regression coefficients (i.e., betas) is tested using the Wald chi-squared statistic (Table 6). According to Table 6, all the predictors in Model 3 showed significance except for OryxMixed. Conversely, in Model 4 the interaction effect is not considered significant when using the Holm-Bonferroni correction. It is the second largest effects so would need to be $p< 0.025$, therefore, any p-value larger (OryxMixed) is also not significant.

Table 9: Evaluation of Models using ANOVA Type II.

	Model 3				Model 4		
	Df	X^2	$Pr(>X^2)$		Df	X^2	$Pr(>X^2)$
Altitude	1	42.903	0.000	dB	1	49.156	0.000
Pass	1	11.818	0.001	Pass	1	14.337	0.000
Drone	6	42.595	0.000	Drone	6	40.875	0.000
GiraffeSingle	1	13.065	0.000	GiraffeSingle	1	13.297	0.000
ZebraMixed	2	14.471	0.001	ZebraMixed	2	14.295	0.001
OryxMixed	1	0.025	0.873	OryxMixed	1	0.000	0.994
ZebraM:OryxM	1	9.216	0.002	ZebraM:OryxM	1	9.074	0.003
Altitude:Pass	1	10.279	0.001	dB:Pass	1	4.766	0.029

Goodness-of-fit statistics: Like the previous models, three inferential goodness-of-fit tests were performed on the model: the Lipsitz goodness of fit test, the Pulkstenis-Robinson chi-squared test, and Pulkstenis-Robinson deviance test. Table 7 below shows the results of the tests. The Lipsitz test yielded a (model 1 = X^2 (df=9) of 10.852, model2 = X^2 (df=9) of 12.442) and was insignificant ($p>0.05$), suggesting the models fit well to the data confirming the null hypothesis.

Similar findings were concluded with the PR Chi-Squared test and the PR deviance test both yielding significant values ($p>0.05$) and confirming the null hypothesis that the model is a good fit to the data.

Table 10: Goodness-of-fit Tests.

	Model 3			Model 4		
	X^2	df	p-value	X^2	df	p-value
Lipsitz	10.852	9	0.286	12.442	9	0.190
Pulkstenis-Robinson X^2	12.904	12	0.376	7.777	12	0.802
Pulkstenis-Robinson deviance	16.012	12	0.191	10.035	12	0.613

Validation of predicted probabilities: Table 10 presents the predicted probabilities. The resultant predicted probabilities were then compared with the actual outcome to determine if high probabilities are indeed associated with events and low probabilities with non-events. The degree to which predicted probabilities agree with actual outcomes is expressed in the classification table (Table 10). The overall correction prediction was 64.6% for model 3 and 61.0% for model 4, a great improvement over the chance level (33.3%).

Table 11: Classification Table.

Observed	Model 3 Predicted				Model 4 Predicted			
	No Response	Alert	Movement	% Correct	No Response	Alert	Movement	% Correct
No Response	124	34	6	75.6	124	30	10	75.6
Alert	34	72	9	62.6	44	61	10	53.0
Movement	15	24	27	40.9	20	21	26	38.8
% Correct	71.7	55.4	64.3	64.6	66.0	54.5	56.5	61.0

DISCUSSION

As stated previously, the 4 models were chosen because of their Akaike information criterion (AIC) score relative to other models containing different sets of predictors. Model 1 (619.59) and Model 2 (618.95) had the best AIC scores and were very close in value for the models without interaction effects. Both models were retained for analysis and from which to evaluate the key

predictors. It was important to first analyze the predictors without interactions to understand how the predictors alone effect the Response, after which the interaction effects were added and their influence on the models evaluated. When the models were developed with interaction effects the scores were not quite as close and the score for the model containing altitude instead of sound intensity scoring lower (Model 3: 606.59, Model 4: 611.61). Model 3 had the best AIC score and the highest overall prediction at 64.6%. One last thing to note about the models was that they consistently, across all four, predicted more false positives than false negatives of the incorrect predictions. This was to be expected as there were a lot of other factors in the natural habitat to create response. It was also expected as a species will generally react in most circumstance over not reacting due to the consequence. It is in the animal's best interest to react to an undetermined threat as the consequence could be grave for not reacting while the opposite is not true. And on the same note, these models were not meant for predictive purposes, but to understand the influence of UAVs more generally on ungulate species.

Species: From the models we see that both Giraffe in single species herd were significant as well as Zebra in mixed herd environments. The Giraffe did not violate the proportional odds assumption. This means that the odds of inducing a No Response reaction over an Alert reaction is equal to inducing an Alert reaction over a Movement reaction. The given values single species giraffe had an odds ratio of 3.05 with a 95% confidence interval ranging from 1.581 to 5.871 in the no interaction model and 3.62 with a confidence interval ranging from 1.802-7.266 in the model including interaction terms. Both terms do overlap and are found within each other's confidence intervals. Figure 2 shows the predicted probabilities of response of the Giraffe adjusted for Altitude = 35m, Pass = 3, Drone = Phantom 3, ZebraMixed & OryxMixed = False.

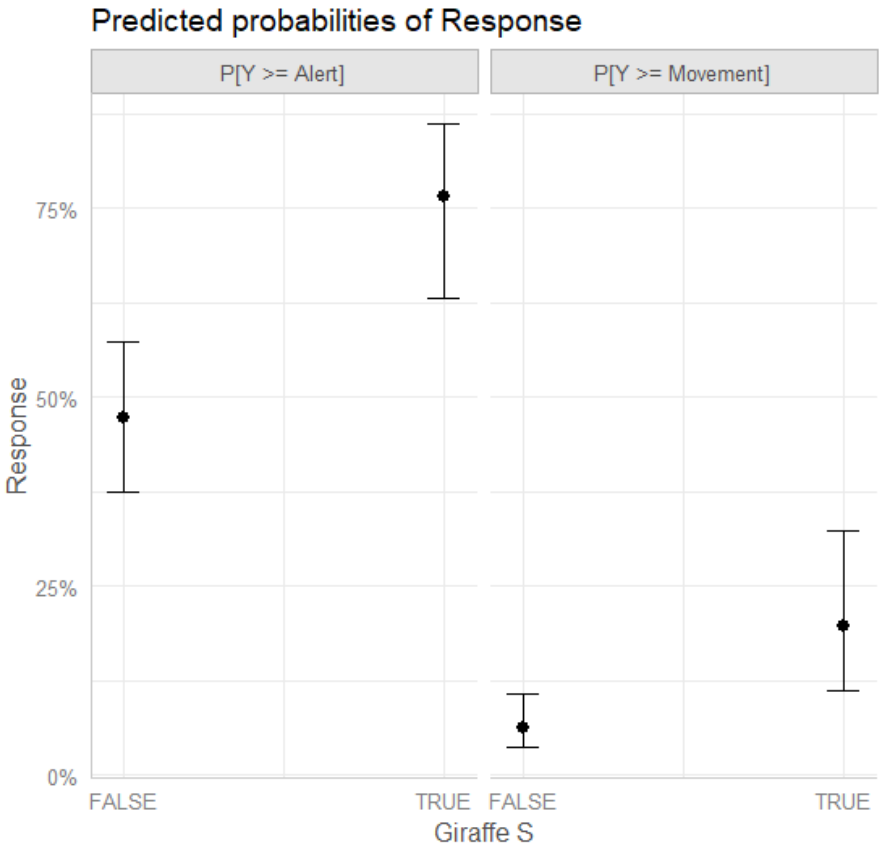

Figure 2: Predicted probabilities of response by Giraffe.

More interestingly, the Zebra was found to have a significant effect in mixed herd environments and the interaction term was significant between the Zebra and Oryx in mixed herd environments. Figure 3 shows the predicted probabilities of Zebra and Oryx in mixed herd environments adjusted for Altitude = 35m, Pass = 3, Drone = Phantom 3, Giraffe Single = False.

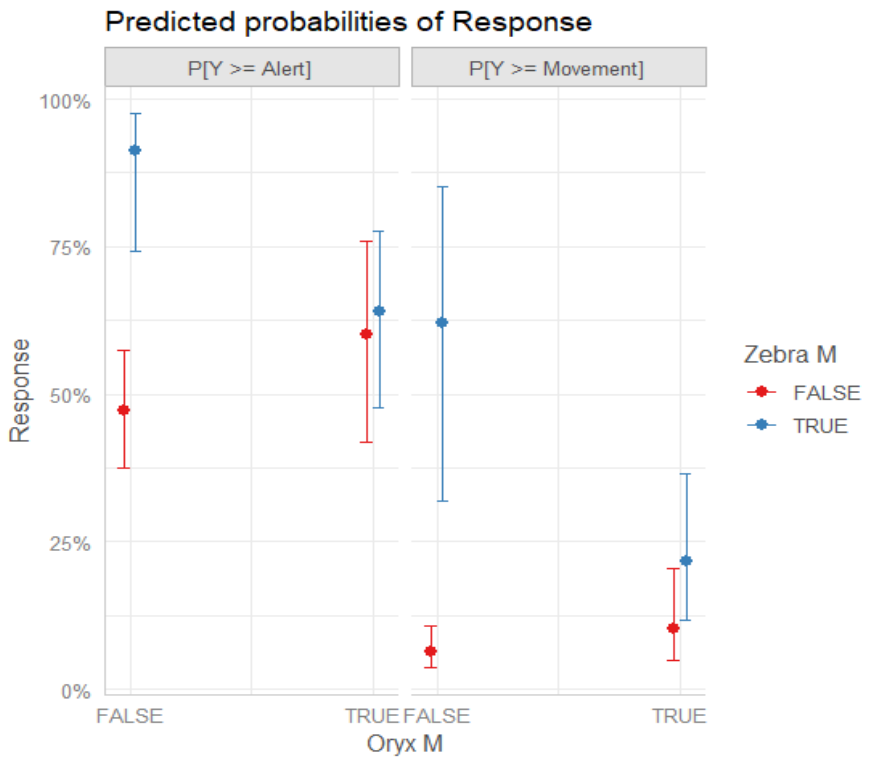

Figure 3: Predicted probabilities of Zebra and Oryx response in mixed herd environments.

The response is found to be similar when Oryx is in the mixed herd environment as well as the Zebra. This is not found to be the case when Oryx is not present. The Zebra in the mixed herd environments without Oryx create a much higher probability of response than without them. This indicates that some species do react more than others, just like Giraffe in single species environments and also implies that some species (Oryx in this case) can mitigate the reaction. While Zebra may normally be a more reactive species, when Oryx is present in the mixed herd, they become less reactive or may look to the Oryx as to their perception of the threat. This also may also be attributed to different species comparative fitness levels in the mixed herd.

Drone: There were considerable differences with the different drones found in the suite from size, speed, sound profile, to mode of flight. Through these differences the predictor was tested

to see if any drone created a higher response compared to other drones. The Phantom 3 was considered the reference drone in most of the previous calculations, but we can see how the species response would vary considerably based on the drone flown. Figure 4 shows the predicted probability of a greater than or equal response to Alert on the left and Movement on the right for each Drone and is adjusted for and Altitude = 35m, Pass = 3, Giraffe Single = False, and Oryx Mixed & Zebra Mixed = False.

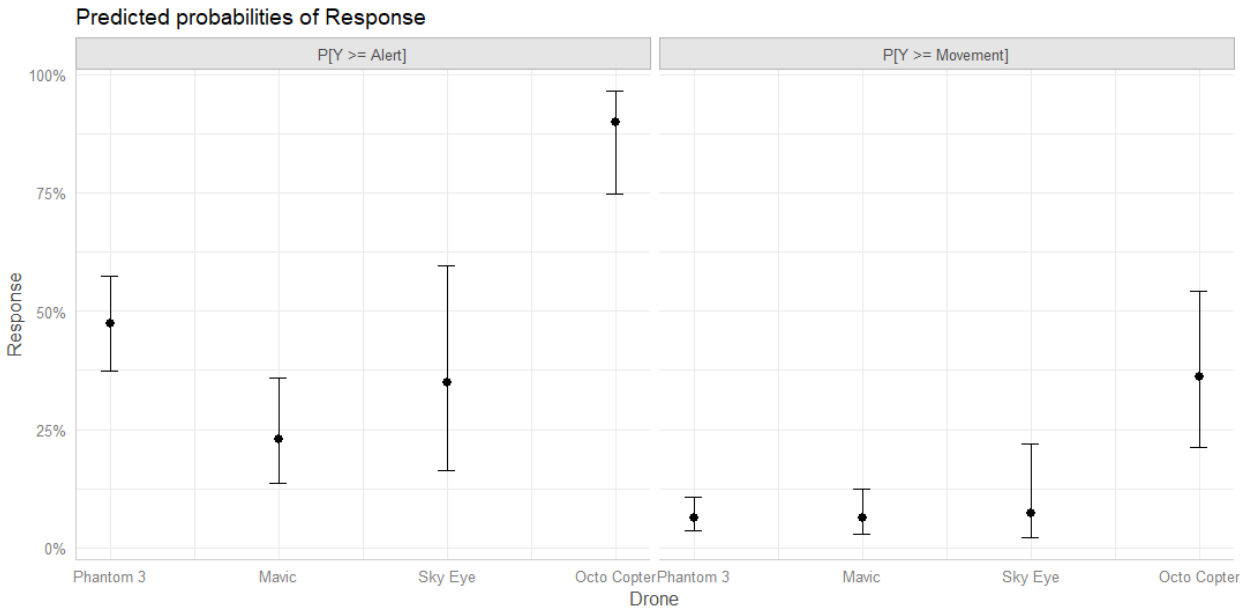

Figure 4: Predicted probabilities of Response based on Drone type.

The Custom X8 (Octo Copter) has a significantly much higher probability of inducing a response. The Proportional odds assumption was not met for the predictor Drone so the odds of inducing a response vary between the two interaction interfaces. The Custom X8 has a 90% predicted chance of inducing an alert response with the 95% confidence interval encompassing up to 96%. That is considerably higher than the other drones. One other interesting thing to note is that the drones do not have consistent response rates. While the Phantom 3 is much more

likely to induce a greater than or equal to Alert response than the Mavic, they have very similar probabilities of inducing a Movement response. This shows that there may be several aspects to the drones that affect the response of the ungulates. For instance, that the sound intensity may alert the species more often, but that close proximity may induce a movement response.

Altitude and Pass: Pass was considered to understand the reaction based on the drones continued presence in the area. The drone would continue passes until the battery was too low or the herd had left visual range. As seen in model 3, there was a significant interaction effect between Altitude and Pass. The figure below shows the predicted probabilities based on altitude and pass adjusted for Drone = Phantom 3, Giraffe Single = False, OryxMixed & ZebraMixed = FALSE.

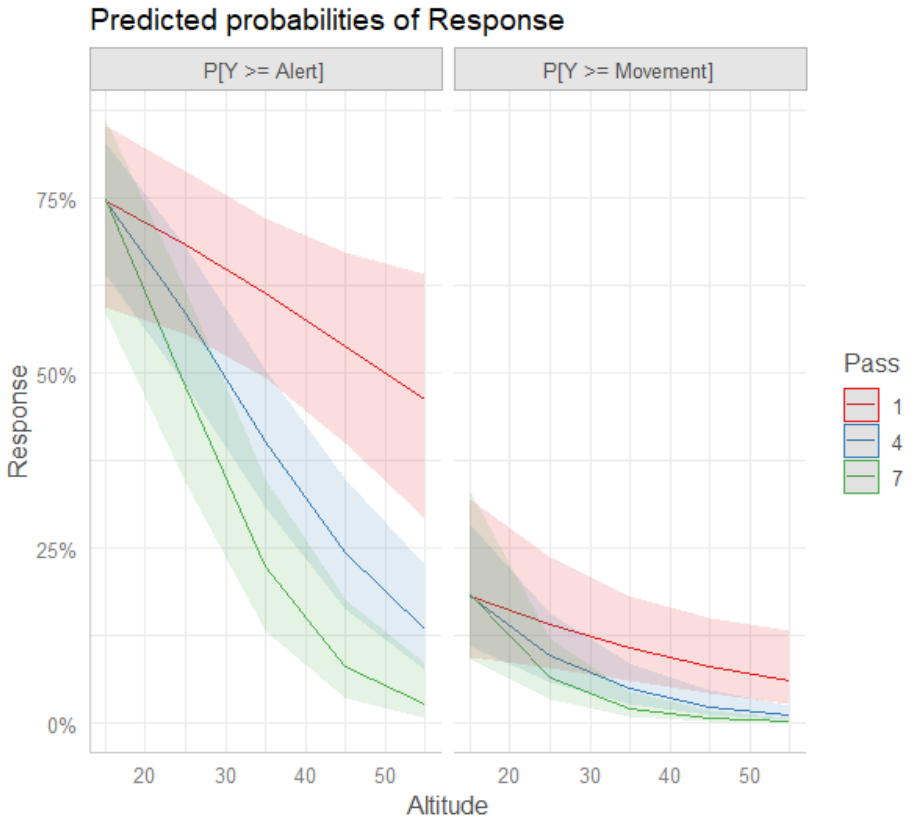

Figure 5: Predicted probabilities based on UAV Altitude and Pass number.

As seen in Figure 5, species response drops significantly based on the number of passes unless at low altitudes. This suggests that the ungulate species undergo rapid habituation to the drones. This was expected as ungulates do not have any aerial threats. The presence of the drone likely alarms them, but they very quickly settle once they perceive that the drone is not a threat. However, once the drone reaches a certain low level of altitude, the ungulates likely don't ever become settled, or it may just take considerably longer to become settled at such close proximity. This is like an ungulate perceived threat from other vehicle types approaching (e.g., cars). In very remote areas, ungulates respond much more reactively than those in areas of highly trafficked areas.

Altitude vs Sound Intensity: While the sound intensity models do fit well with the data, the authors believe the evidence is not compelling enough to ascribe the animal response to sound intensity over Altitude. The most telling sign was that the coefficients (betas) for each drone from the model associated with sound intensity was different, and in the case of the Mavic compared to the Phantom 3, it showed significant. Furthermore, from the drone reaction, based on some of the differences in response levels from different drones at similar altitudes, there appears to be factors at play other than from the drones. Therefore, altitude as a predictor likely encompasses more of these factors as proximity (intensity) to varying characteristics likely plays a role as well.

The interaction effect between sound intensity and pass was not significant which was also telling. If the animal is becoming habituated to the vehicle flying overhead within that period of time, it would be anticipated that they would also become capable of enduring slightly more of

the effector (i.e., sound intensity) like we see with Altitude. For instance, if the drone passes over the second time at the same altitude, what we are seeing is that it will induce less of a response. It would be sensible to say that there is some altitude below that the drone could pass on the second pass to induce that same probability as the first pass, which we see in the data. This same interaction would be expected from sound intensity, if sound intensity where the leading factor over altitude, where there is a higher sound intensity on the second pass that would create an equal probability of response as the first pass, which we do not see.

Sound intensity was added as a predictor because of the much higher responses to the Custom X8. The researchers believed that because it was considerably louder it may be what was the contributing factor over altitude alone. Therefore, the sound profiles of the vehicle were measured in an anechoic chamber under similar conditions to attempt to differentiate between the different levels of inducing responses.

General: The field unit observed in individual cases the effect of their proximity to the UAV, the time of day, and whether or not the UAV appeared to be competing with attention of a larger source of danger. Vehicles that drive by, nearby baboon/cheetah walks, and weather all appeared to influence the responses, as well. General species behavioral patterns influenced the results, too. Generally, most ungulates graze or browse in early morning and in early evening/late afternoon, allowing them to avoid the heat during midday, during which they hide from predators under the shade of trees. Some ungulates are browsers (eat leaves) and are found in thick bush, so they are more difficult to spot and observe. Others are grazers, found in open grassland, and therefore are easier to spot. Impala and Kudu numbers were lower simply because fewer of them

are free ranging on the property. Kudu are very cryptic/elusive animals, often hiding in bush cover in small herds. Most of the data were collected from larger open areas where the animals were easier to locate and where they could be observed from a distance without disturbing them prior to take-off. We noted differential responses for some species when in single species groups versus in mixed species groups. For example, the Zebra are flighty when not with other ungulates but appeared to react just like the Oryx when with them. The Giraffe were observed to be flighty when first passing over them but became habituated to the UAV presence after just two passes.

More generally, pertaining to animal habituation to humans and traffic, we used vehicles to transport ourselves and the vehicle traffic appeared to affect the responses. We observed the animals to be flightier in areas that are closer to more traveled roads, and it was difficult to collect data close to neighboring farms that allow game hunting since the animals there were flighty when sensing human presence. Male responses may have also differed from female responses. For example, some male springboks may have suppressed their flight responses to keep hold of their territory while the females and maternity herds exhibited a flight response.

SUMMARY AND CONCLUSIONS

This article reports on the behavioral responses of free ranging ungulate species (Oryx, Kudu, Springbok, Giraffe, Eland, Hartebeest, and Impala) housed in an animal reserve in Namibia to the presence of different UAV models. The study included 99 flights (346 passes) at altitudes ranging from 15 m to 55 m. The results suggest strong correlations between flight altitude and

animal response across the different ungulates and the evidence suggests rapid habituation to the UAVs.

The single herd and mixed herd observations conducted in the study provide evidence in support of the feasibility of aerial wildlife monitoring (AWM) by UAVs. The highest percentage of responses that did not invoke movement occurred at the highest altitudes and was seen that the longer the drone was in the presence of the animals the less likely they were to negatively respond. As seen with the reference vehicle, Phantom 3, there was a less than 7.5% chance of inducing a movement response at 55 meters. Additionally, after the average number of passes (4.5) while flying at 55 meters reduces the predicted probabilities of inducing an alert response or greater from 46% to 10% and a movement response from 6% to 1% or an average reduction of approximately 80%. Furthermore, the type and size of UAV plays a large role in the response of the animals. The factors that contribute the most are not exactly known; however, sound profile (i.e., sound intensity, frequency), size, and style of flight (i.e., multirotor, fixed wing) likely play a roll. The study did not conclude any long-term effects of the habituation of the drones because it was very difficult to confirm that the same animals were being flown over on each subsequent day. This was due to the large size of the property and substantial number of animals. Further study of habituation to the presence of UAVs could further strengthen the results including studies monitoring the same animals over extended periods of time.

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CHAPTER 3

The Roles of UAS & Domain Expertise in the Deployment of UAS within Organizations

INTRODUCTION

Bringing UAS into professional organizations has generated a new challenge that is of growing importance to industry. Registered user data from the FAA shows a sharp increase of registered UAVs from 138,000 in April 2015 to 1,550,000 in February 2020 – an increase of 1100%. In the early boom of the personal UAV, privacy and safety concerns received a lot of attention in the public eye. Kwon and Park (2018) found that the adoption of emerging technologies is affected by social norms and values, specifically citing UAVs for their distinctive characteristics, highlighting how safety concerns may be resolved through regulations. During that time, UAVs were regularly finding their way into new use research. Many of the use cases fell into the broad areas of mapping (e.g., photography, photogrammetry, scanning, surveillance, inspection) and transportation (light aircraft, delivery). From an extensive analysis of wildlife research, Chabot and Bird (2015) found, "UAS are particularly well suited for collecting data at an intermediate spatial scale between what is easily coverable on the ground and what is economically coverable with conventional aircraft." Chen, Laefer, Mangina, Zolanvari, and Byrne (2019) expressed that imagery-based, three-dimensional (3D) reconstruction from unmanned aerial vehicles (UAVs) holds the potential to provide safer, more economical, and less disruptive bridge inspection. Gonzalez et al. (2016) used UAVs to acquire test flight footage to compare to ground based video data to perform object detection, classification, and tracking of wildlife in forest or open

areas. Beck et al. (2020) evaluated the potential risk, reward, and impact of drone transportation on the stability of adrenaline during episodes of anaphylaxis.

More broadly, the process by which an organization deploys new technology is critical to the success of that technology over the long run (Birken et al., 2017). Furthermore, beginning with a strong technology and a strong strategic plan are the cornerstone of four main considerations coupled with deployment (Mirvis, Sales, & Hackett, 1991). In fact, as described by Markus (1984), many companies have been surprised at what it takes to make technology "work" and have not planned for the many complications and consequences.

Cooper and Kleinschmidt (1994) found that "the greatest differences between winners and losers are found in the quality of pre-development activities." The fuzzy front end, a term made popular by Smith and Reinertsen (1991) roughly describing the development stage from the generation of the idea to the approval for development or termination, determines which projects the organization will execute. At this early stage, one focuses on quality, costs, and timing while the initial effort to optimize is low, even though its effect on the whole innovation process is high (Verganti, 1999). Thus, a deeper understanding of the fuzzy front end and its impact on new product development success can help an organization to be more effective in its development efforts.

Proper preparation and focus on the deployment process can help ensure success and mitigate extraneous use of time and resources. Iteration is a fundamental part of the development process. Martinez Leon, Cross, Letens, and Hernandez (2013) found that iterations constitute a major part

of new product development lead-time and cost – a key driver of scheduled risk, and a major source of uncertainty in the commitment of resources and the delay of a project. Wynn and Eckert (2017) believe that, although given a substantial amount of research attention, a consensus model or terminology for describing iterative situations has remained elusive despite the fact they believe perceiving design and development as an iteration process is necessary to understand the process. Additionally, they believe that within the different subsets of literature they do not all strongly cross-reference each other, especially those examining micro- and macro-level iteration and those considering the different development domains. Furthermore, Ahmed, Wallace, and Blessing (2003) found that both novice and experienced designers tend toward a much different design approach where the novice tended to use the particular pattern of *trial-and-error*, while the experienced designer used particular *design strategies*.

As it pertains to UAVs, Hildmann and Kovacs (2019) expressed that a large factor that stands between UAVs and their widespread adoption is *not* a shortage of viable applications or the availability of parts, but a number of other challenges, including those associated with their operation. Austine (2010) described a UAV deployment process with a focus on vehicle airworthiness and safety aspects. The focus was regulatory as was much of the previous literature. They, as well as the literature, did not focus on the organizational aspect of deployment (e.g., how UAVs are deployed within the organization through training and management). This article presents a framework for the process of deployment of UAVs in organizations, drawing from general methodologies for innovation with a nonregulatory focus. The framework presented in this article leans on two case studies. The objective in the first case

study was to count animal species in the African savanna and the objective in the second case study was to deploy drones to assist with anti-poaching efforts in the African savanna.

The article is organized as follows: Methodology describing the deployment process with a focus on development and testing, Results and Discussion providing a short description and results from the 2 case studies, and Summary and Conclusion giving practical implications.

METHODS

Let us frame the introduction of UAS into an organization as a process of innovation, consistent with models of innovation found in the literature (e.g., Birken et al., 2017; Mirvis et al., 1991). The organization's deployment of unmanned aerial systems framework is divided into six evolving steps encompassed by three main stages. It is important to execute each stage thoroughly to reach a successful outcome. Figure 1 displays the six steps and illustrates how the process cycles through learning and modifying.

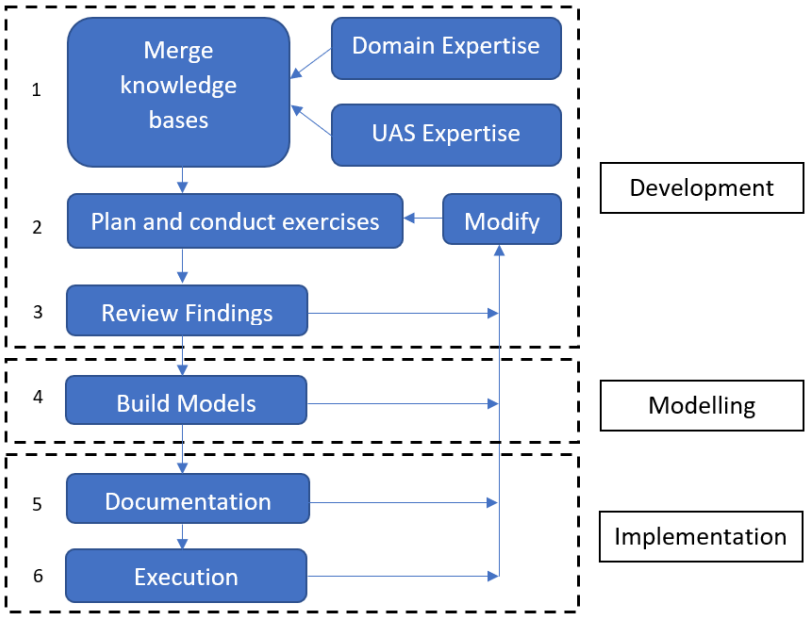

Figure 1: Three-stage Diagram.

This article will focus on the first two stages of the deployment – development and modelling. During those two stages of development, it is important to settle on general size and complexity. The UAS specialist recognizes that in unmanned aerial systems increasing complexity accompanies high investment cost and that the goal is to focus on keeping size and complexity down while still achieving performance goals, and that can be achieved with high reliability. Figure 2 below is a graph used to illustrate how increasing size and complexity can lead to an increased need for higher reliability.

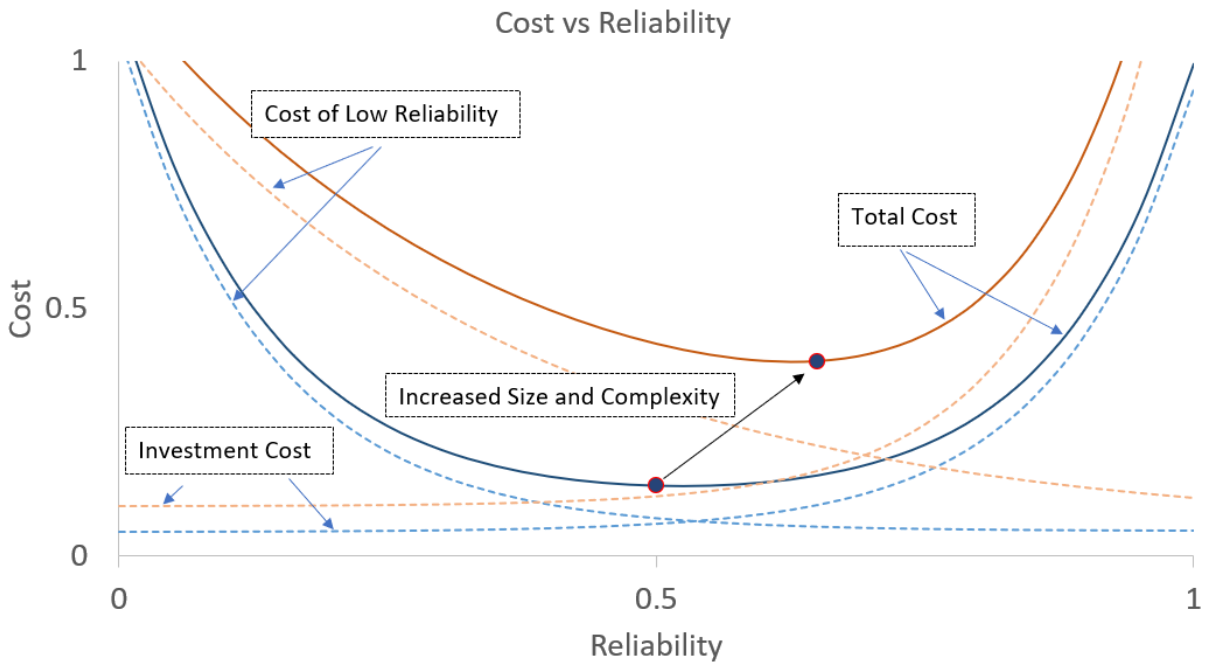

Figure 2: Cost versus Reliability with increasing Size and Complexity.

The cost of low reliability of a UAS is a hidden operational cost, and when size and complexity increase that cost only increases more. As size and complexity increase, the pitfalls are many. Part costs, number of parts, person-hours for repair increase rapidly, procedures become more involved, training becomes more difficult, and more expertise is required. On the other hand, cost of investment increases with reliability because the design process during deployment

becomes more complex when striving to reach higher reliability goals. Figure 2 shows this trade-off. The blue lines correspond to one UAS system and the orange lines to a more complex one. As shown, the more complex system has a higher investment cost and a higher operational cost. Notice that the theoretic design point of the more complex system (the minimum cost point) has a higher total cost and is more reliable than the less complex system. However, the cost of low reliability is a recurring cost that continues after the deployment phase has ended. Throughout the evolution of the design, it is important for both the UAS experts and the domain experts to remember that the goal is to attain a high level of reliability. Figure 3 shows how reliability evolves through time during the deployment.

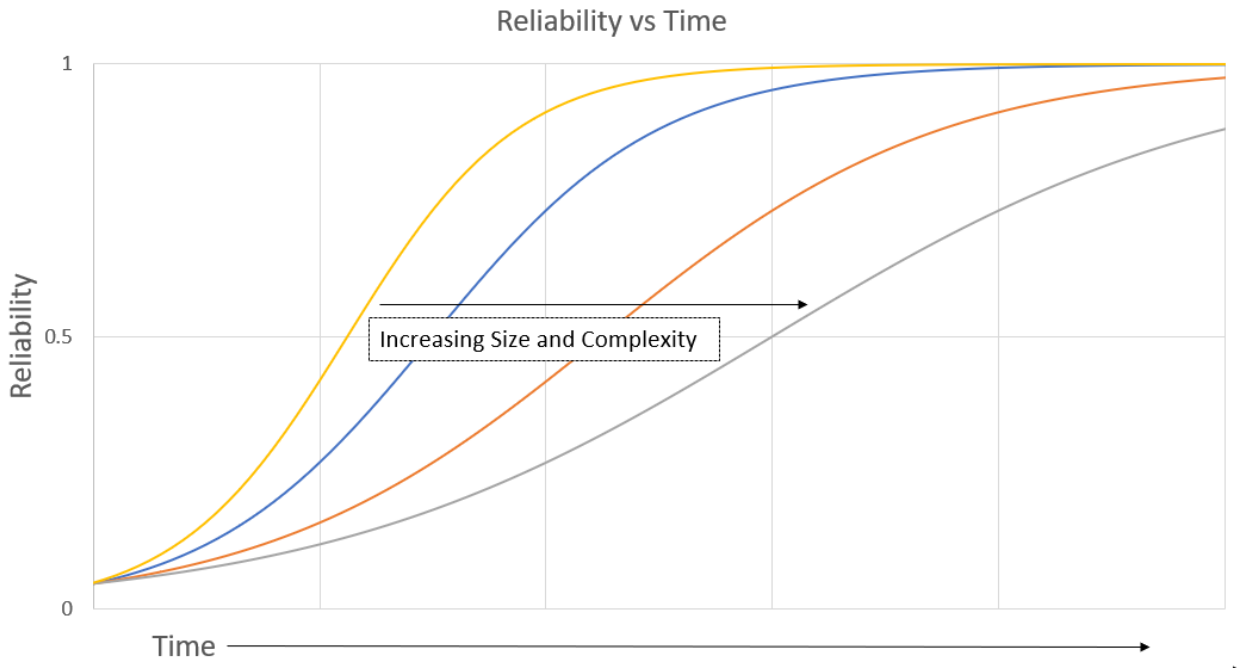

Figure 3: Reliability through Time.

As shown, increased size and complexity slow the progress of system reliability. In the end, the overwhelming goal is to increase performance while reducing cost. One obtains that cost reduction by maximizing reliability during the deployment process – thereby avoiding all of the

earlier mentioned pitfalls of low reliability. The domain experts and the UAS experts need to keep these objectives in the forefronts of their minds as they go through the different stages of deployment.

Stage 1: Development

1. Merge knowledge bases: The first step in the deployment process is to merge organizational expertise and UAS expertise. During development, the group of individuals holding one expertise must understand the needs and constraints of the other. Quite naturally, the individuals with the organizational expertise initially have little understanding of the pertinent UAV constraints, and the individuals with the UAV expertise initially have little understanding of the organizational constraints, despite the two sets of constraints being highly coupled. The organization is attempting to implement UAVs to improve an existing task (lower cost or improve efficiency) or to develop a new task within the organization. Knowledge within the organization is the driver for how the UAV may accomplish this task. Those within the organization will not have the knowledge to understand the strengths and limitations of UAVs. When not accounted for, this will lead to a lack of appreciation of the complexities of the deployment process. The importance of UAS expertise cannot be understated. Vehicle and system capabilities are a multi-objective optimization problem with no clear solution known in advance. Dealing with balancing detail (resolution), movement (area/time), cost, and reliability (robustness) are complicated, and require understanding of UAS constraints, as well as knowledge about the deployment problem more generally. Indeed, the first step in the deployment process must begin by putting in place a group that holds a broad perspective, one

that has strong understanding of the two fields of expertise, and whose initial task will be to define a way of moving forward.

The domain knowledge of the objective starts broad, and the group narrows down the objective only after digesting the UAS knowledge. How to best utilize the UAS begins with understanding the capabilities needed to accomplish a set of tasks, considering whether they replace an existing set of tasks, contribute to or bolster an existing set of tasks, or whether they are needed to create of a new set of tasks altogether. The process best progresses in tandem with implementation, during which the UAS slowly takes over more elements of a process. See the Action Chart in Table 1. It gives a breakdown of the organizational expertise and the UAS expertise relative to the objective.

The domain experts may also need to bring in individuals and data pertaining to other existing approaches. For example, later in this article we will discuss best practices in surveying the African savanna by aircraft and helicopters. Understanding these best practices is critical to understanding how one can survey the savanna by UAS. The involvement of individuals who have expertise in existing approaches, that may or may not compete with the UAS approach, can be beneficial in several ways. Both customers and individuals within an organization can be initially skeptical of the employment of a new technology before it has been proven in the given domain. Later, there may be a need for new customers to accept it, too. Involving individuals with expert knowledge of an existing approach can assist with the deployment process and later assist with the transition to market acceptance. A managed transition from employing an existing approach to the UAS approach can be a viable part of a deployment strategy.

Table 1: Action Chart.

Organization Expertise	**UAS Expertise**
Object properties Living and inanimate objects, such as humans, animals, and buildings; includes understanding of their characteristics, and interdependencies	***Vehicle properties*** Size, type, launch and landing site constraints, shape, noise, power source, endurance, tradeoff with sensor payload, weight
Field Properties Site survey size, terrain, launch and landing availability, elevation	***Sensor (camera) properties*** Lenses, pixels, weight, size, spectrum, memory, video/still
Organization Operations **Division of labor:** Personnel's role in launching, flying, communications, observing **Management*:*** Performance strategies, resource allocation, tactics, personnel, training, quality control (reliability) **Personnel:** Leadership, technical support, maintenance, operators **Training:** Methods, continuing education, assessment	***UAS Operations*** **Flight path planning:** Autonomous (predetermined decision) versus RC (real-time decision) **Networking:** Range, nodes, communication, transmission of data (live vs recorded) between UAV and ground station and groups **Data processing:** Post processing speed **Piloting:** Instruments, flight checks, vehicle operation

Those within the domain of an organization understand the environment in which the UAS will operate. Understanding that environment is critical to deployment. For example, in the previously mentioned problem of surveying the African savanna, the savanna is a heterogeneous medium of fields, bushes, and animals. The animals interact with the fields and the bushes. The

animals are of different types, each type has a level of abundance, and each interacts with the fields and the bushes differently. When the goal of the aerial survey is to count animal species, understanding how each animal species interacts with the fields and the bushes become critical to the effectiveness of the UAS approach. The animal species hide from view depending on the level of bush cover and the type of bushes. The locations where they are observable depends on their hiding behaviors, which depend on what they eat, how they evade predators, and the time of day. All of these factors play a deciding role in the design of the aerial survey and its deployment process.

Similarly, knowing the workforce constraints in the organization can play a deciding role in the design of the survey and its deployment process. The workers in the organization have a given level of proficiency. They may later need to implement the UAS approach, in which case they would need training. Systems deployed in remote locations will need in-house UAS operators, and maintenance and repair capabilities.

At the initial development stage, the UAS knowledge of most importance pertains to vehicle, sensor, and operational capabilities and understanding the benefits and limitations of the different designs. The group tackles this multi-objective problem by comparing the different requirements that can meet the given objective. For example, if the UAV has limited takeoff space but requires high range and endurance, the UAV expert may recommend a VTOL (vertical take-off and landing) fixed-wing platform in order to exploit the fixed-wing vehicle's endurance while maintaining low takeoff and landing space. If the UAV system is required to be highly robust and reliable, perhaps because of its use in remote locations, then the UAV expert may

recommend a different solution in order to avoid the complexity of maintaining and repairing a VTOL fixed-wing platform. As part of the deployment process, an organization can form a dependency chart once the groups have suffused their knowledge (See Figure 3). The group would create the chart by laying out requirements. The purpose of the dependency chart is to identify the key decision points they will need, and to try to understand how they affect the different aspects of the deployment. This can be as simple as choosing flight altitude. Continuing with the example of counting animal species in the savanna, the altitude of a vehicle impacts a number of important variables in the setup of transects of flights – specifically the strip width and the level of animal disturbance. Note, even in this simple example, that both organizational and UAV information are critical, reinforcing the importance of the need to merge organizational knowledge and UAS knowledge from the start. Through the process of laying out individual intersection points, the group gains insight into where initial assumptions must be made, the variables that can be tested in the first iteration of testing, and where the system might be modified to better meet the objective.

The final step in merging the knowledge bases is to use the insights gained through the dependency chart to optimize the vehicle for the desired mission. This is done by mapping out dependencies to make sure that the designer understands the intersection points, followed by tabulating the impacts to keep track of the dependencies. Figure 4 below is an illustration of the mapping intersections between systems properties and operations and how interdependent the system can become.

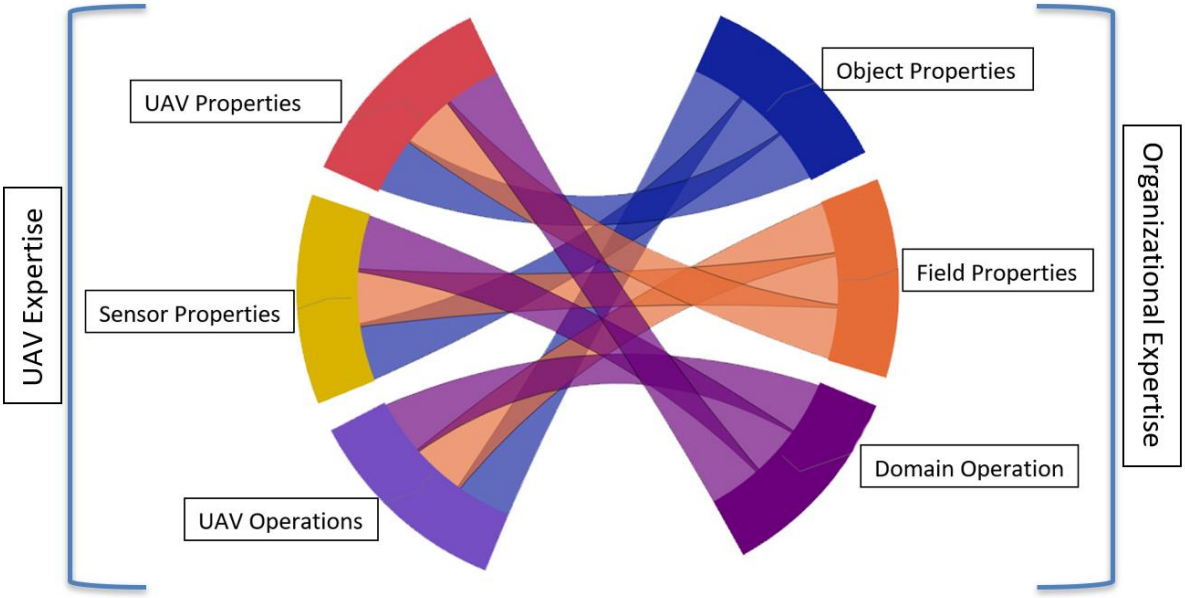

Figure 4: Dependency Chart.

One accomplishes this in practice by then defining minimum requirements to perform useful work. This begins by increasing the capabilities of desired features, followed by identifying and mitigating points of concern (high risk, high cost, and low reliability). System design is completed as failure points are kept to a minimum. In the end, the most robust solution is found away from constraint boundaries.

These ideas can be illustrated by continuing with the previous example in which a VTOL fixed-wing vehicle was ruled out due to excessive complexity, the vehicle still needs to meet certain endurance and range capabilities and the ability to take-off and land in a small area. The solution might be a PTOL (point take-off and land) fixed-wing vehicle – a designation given to small fixed-wing aircraft that have the capability of very short take-off and landings – making it a suitable choice. A UAV designer may then decide to fix the design to a vehicle that has these

characteristics and then focus on other design parameters aimed to increase range and endurance. For example, the designer may want to consider employing a larger wingspan to reduce flight speed and therefore drag losses, increase payload capabilities for larger fuel load, or focus on motor and propeller characteristics for propulsion efficiency. When identifying and mitigating points of concern, the UAV designer looks for small changes in the system (inputs) that create large improvements in cost, performance, or reliability (outputs). For example, to accommodate prohibitively large sensor errors that result from large roll or pitch of a vehicle, the UAS designer might consider a number of options: eliminate flights under high wind conditions, place the sensor on a gimbal, or post-process the flight data. Lastly, the designer must try to identify and limit failure points. One such failure point with fixed-wing aircraft occurs at take-off. The designer can reduce the risk of this failure point by decreasing the vehicle's speed at take-off. The designer might accomplish this by adding flaps to the vehicle, by which the stall speed decreases and so too the level of thrust at take-off decreases.

2. Plan and conduct exercises: In this step, the UAV designers begin to plan and conduct preliminary exercises. They test integrated knowledge as a proof of concept. The UAV designers develop the tests, not only to assess a system's proficiency, but also to identify key unknowns. While it may seem obvious, many of the key unknowns arise in actual implementation. So, it is important *not* to create an environment free of uncertainties. An early goal of the test design is to identify the difficulties that arise from those uncertainties to give the developer more opportunity to address them in subsequent testing.

With each iteration, the system is being scaled up and becoming closer in nature to the system that will be deployed. One cannot stress enough that the UAV developers are developing a UAV system that they will need to integrate into their organization. Therefore, the developers must maintain input from the group having domain expertise throughout the process to ensure that their solution is consistent with the organizational perspective.

3. Review findings: The last step in the development process is about learning. Here, the developers review their findings from the exercises they conducted. Presumably, the group has now illuminated the key factors and has arrived at a better understanding of costs, risks, and time. The group fits the new information into existing processes and constraints. The relationship between organizational processes and constraints and the new information sheds light on the viability of the solution options. Some options will be easier to integrate into existing processes, and some will meet organizational constraints (personnel, equipment, management, time, costs).

Stage 2: Modelling

After completing the development process, the second stage of deployment is to take the development process and *codify* it into a process model. The modelling of a UAS system enables the effectiveness of the process to be assessed in more detail and, with that information, to learn how the parameters in the system affect performance, cost, and reliability in different settings, and therefore how it meets their objectives in the different settings. Understanding how the system behaves in different settings creates a deeper understanding of the impact of the key factors determined in the previous steps. For example, through intuition, a developer may believe one variable to have a much greater impact on the output of the system than it really has. The

process model can expose the correct level of impact of that parameter. In the results section, you will see the development of process models in two case studies. As you will see, the process models typically contain an important level of randomness. That randomness plays an important role in the process model and is in fact responsible for the trends that the process model reveals. You will see that the impact of the UAS objective is difficult to appreciate without the process model. Therefore, it is best for the UAS developers to study the process models and understand the trends they reveal before circling back to conducting more exercises or before developing documentation procedures for the system.

Stage 3: Implementation

This article does not focus on this final stage of the deployment but, for completeness, a few words about this stage are in order. First, the goal of implementation development is to provide guidance for the execution of the process, realized by documenting procedures and by developing appropriate levels of training. Implementation requires an integration of the new system into the organization's structures. The developers are adding new procedures to existing procedures as it pertains to hiring, training, procurement, and so on. During implementation, the UAV designers are codifying system inputs, outputs, and requirements. The implementation development begins with setting precise expectations of design requirements as deliverables - what the system produces and at what level of accuracy. The developers are defining the expectations surrounding a properly functioning system. Different implementation sites will have different requirements and expectations. The sites will differ by their object properties, field properties and local operational properties. Each site will require customization for a properly functioning system.

The process of executing the system is the final step of full integration into an organization and it is possibly the most difficult part of implementation. This is where the organization goes through hiring, training, operations, and maintenance and sets up guidelines for these practices. The most important take away may be appreciating, while this is the last step in the deployment cycle, that executing the system constitutes the beginning of a continuous process of improvement – one that requires continued learning, continued evolution of requirements, and continued involvement of those who have both organizational and UAV expertise.

RESULTS AND DISCUSSION

This section describes two UAS development and modelling case studies; the objective of the first is aerial counting of high-valued animal species in the African savanna and the objective of the second is aerial surveillance for anti-poaching of high-valued animal species in the African savanna. The authors obtained the reported data from studies they performed between 2017 and the present. You will see that the two studies differed in several notable ways. The aerial counting study employed fixed-wing UAVs, the UAVs followed pre-determined autonomously controlled flight paths, and they served as a replacement to aerial counting by aircraft. In contrast, the anti-poaching study employed multirotor UAVs, the UAVs followed real-time radio-controlled flight paths, and they served as a complement to ground surveillance. Despite these differences, both case studies followed the methodology presented of merging UAS and domain knowledge bases, planning and conducting exercises, reviewing findings, and developing an integrated model of the UAS system, as outlined in the method section.

Case Study 1: Aerial counting of high-valued animal species

The aerial counting study illustrates how early insight from experts in both the UAS and wildlife fields is critical to the development stage. The UAS designers first sought to comprehend the important parameters in aerial counting in accordance with best practices using aircraft. The designers learned from wildlife experts that consistency in animal counting drives its performance. The overarching goal in animal counting was to obtain the greatest consistency achievable within their constraints. The UAS designers examined such wildlife parameters as field area, environmental specs (e.g., animal density and bush coverage), animal attributes (e.g., general behaviors, and flee responses), and human factors (animal detection and identification). The UAV parameters that influence consistency were, among others, area, environmental specs (takeoff and landing constraints, altitude, temperature, animal appearance), payload specs (e.g., camera weight, lens, pixel count, video/still), vehicle specifications (e.g., takeoff and landing ability, noise, durability, control), and networking. Field-testing gave the designers the opportunity to examine the wildlife and UAV parameters together, and to examine the corresponding human resource requirements (e.g., pilot procedures and training). The designers then studied the mutual influences of the parameters by conducting animal counting tests in the field, and by reviewing the data with wildlife experts. They determined that the three most important wildlife parameters were sample area, bush coverage, and animal density. Figures 4 and 5 show the dependencies of coefficient of variation on animal density, the size of the sampled area, and the level of bush coverage.

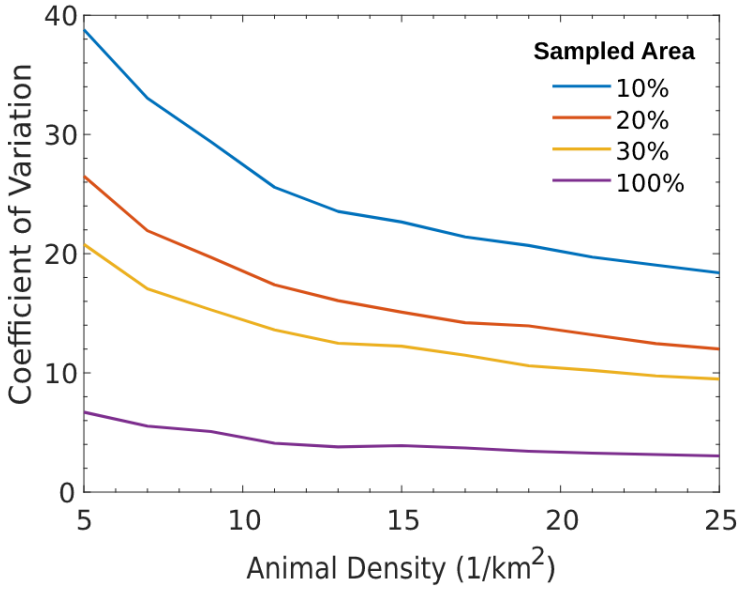

Figure 5: Coefficient of Variation (CV) versus Animal Density for different Sampled Area Percentages.

Figure 5 displays coefficient of variation versus animal density for different sampled area percentages. The data corresponds to a field that has 15% bush coverage. Notice that the CV decreases with animal density, and levels off when the animal density reaches 25 animals per km^2. Also notice, as expected, that the CV decreases as more of the area is sampled, but at diminishing levels. When 100% of the area is sampled, animal movement brought on by the unmanned vehicles is responsible for residual miscounting. In practice, the noise pattern of the UAV would strongly depend on flight conditions with varying UAV speed, direction, and altitude, as well as wind speed and direction – all playing a significant role in sound transmission. This effect was deemed minimal at low sample percentages (<50%) as the distance between sample strips was much larger than observed flight distances. Animal disturbance could become a larger factor in sampling methods with overlap or closely positioned sample strips.

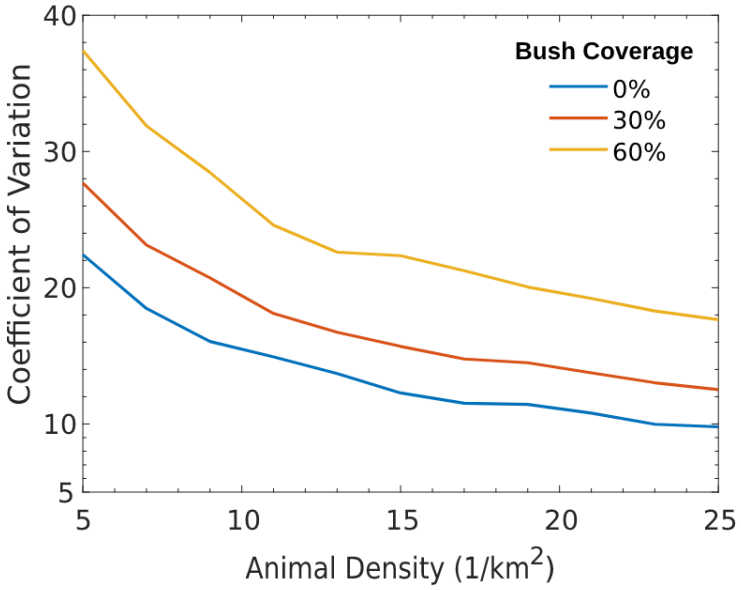

Figure 6: Coefficient of Variation versus Animal Density varying Bush Coverage.

Figure 6 displays coefficient of variation versus animal density for different amounts of bush coverage. The data considered a sampled area of 20% and the same model for animal movement induced by the UAV during counting. Like in Fig. 1, the CV decreases with animal density, and levels off when the animal density reaches 25 animals per km^2. We also see, as expected, that the CV increase with bush coverage. Notice that the difference between CVs over the 0-30% range of bush cover is larger than over the 30-60% range of bush cover. As a rule of thumb, one can find it advantageous to consider the ratio of the amount of sampled area relative to bush coverage, recognizing that 20% sampled area with 50% bush coverage 10% sampled area with 0% bush coverage give a similar CV, putting aside animal behavior patterns.

The field models captured many of the system parameters' interdependencies. The UAV parameters were determined through best estimates and then trial and error in the preliminary designs. Interestingly, some of the field parameters that turned out to be the most important were,

at first, not considered important. Early in the study, the UAS developers considered UAS cost and performance parameters to be more important than reliability. Cost is a driving factor given the high cost of the aerial counterparts – the manned helicopters and the airplanes. The initial design was a small, fixed wing UAV that is hand-launched, and is capable of covering the desired sample area in 4 hours with a high enough pixel density to detect and identify animals. The developers pushed vehicle performance by experimenting with a larger airframe to increase endurance and house a more substantial sensor. This became problematic when vehicle takeoff proved difficult in the high altitude and heat. Similarly, the harsh terrain and vegetation also took their toll on the vehicle. To combat the damage occurring to the vehicle, the designers placed large skids on the vehicles and other protective measures which, in turn, increased vehicle weight and difficulties in takeoff. After confronting many of these issues in the field, the importance of vehicle and component reliability became apparent. The personnel that would ultimately become responsible for using these systems in the field would *not* be those who designed and built these systems. Simplicity and reliability of the system became a higher priority in the development than cost.

Case Study 2: Aerial surveillance for anti-poaching of high-valued animal species

Like in the first case study, aerial surveillance for anti-poaching of high-valued animal species demonstrates how early insight from the experts in both fields is critical to the development stage. Understandably, the main objective in anti-poaching is to catch poacher(s), which one measures in catch percentage, in time to catch. Therefore, the anti-poaching experts helped facilitate a meaningful approach for how the UAS may be practically utilized in both patrol and interdiction scenarios. The UAS designers examined such anti-poaching parameters as field area,

environmental specs (e.g., terrain, bush coverage, hiding locations, weather), poacher attributes (e.g., camouflage, survival time, detectability, capabilities), and human factors (e.g., identification, tactics). The examined UAV parameters that influence the apprehension of poachers were, among others, area, time, environmental specs (takeoff and landing constraints, altitude, temperature), payload specs (e.g., camera weight, lens, pixel count, video/still), vehicle specs (e.g., speed, endurance, takeoff and landing ability, noise, durability, control), and networking. Field-testing gave the opportunity to examine the anti-poaching and UAV parameters together, and to examine the human resource requirements (e.g., procedures and training). The developers identified the most important parameters by conducting field tests followed by careful reviews of the findings. They found the most important parameters in the apprehension of poachers to be property size, shape, number of UAVs, and bush coverage (hiding locations). Figures 7, 8 and 9 show the dependencies of catch percentage on property size, shape, number of UAVs, and bush coverage.

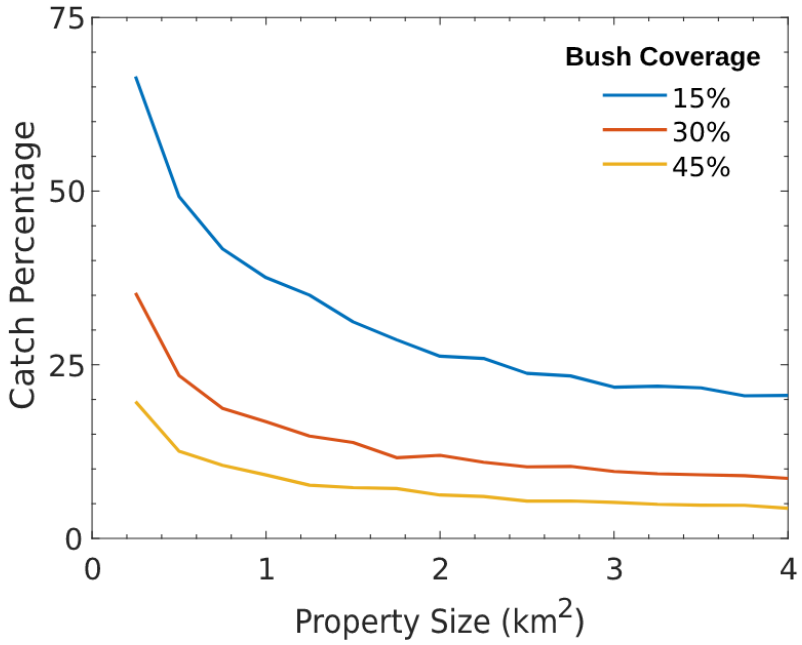

Figure 7: Catch Percentage versus Property Size for different Bush Cover Percentages.

Figure 7 shows catch percentage versus property size for different levels of bush coverage surveyed by 1 UAV on a square property. As shown, the catch percentage significantly drops off as property size increases and then levels off when the property size reaches around 3 km^2. There is a noticeable difference in the catch percentage between the 15-30% range and the 30-45% range of bush coverage. The exposure time of the poacher is longer as he has less area in which to take cover, resulting in a greater opportunity for the anti-poaching unit to detect him.

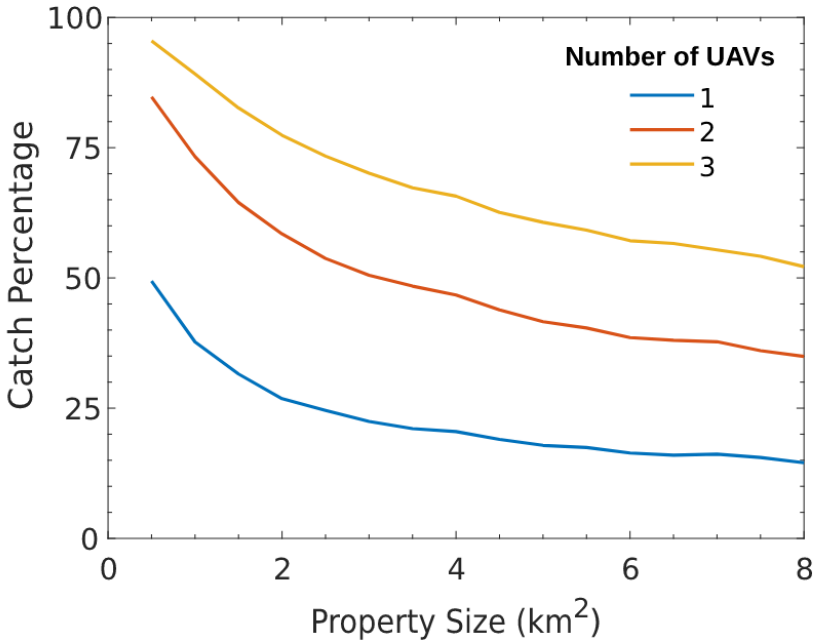

Figure 8: Catch Percentage versus Property Size for different numbers of UAVs.

Figure 8 shows catch percentage versus property size for different numbers of UAVs surveying the area. The property had 15% bush coverage and was square. As shown, the efficacy of adding UAVs has diminishing return. The increased catch percentage from 1 to 2 UAVs is much higher than from 2 to 3 UAVs. The catch percentage is limited at 100 so by continuing to add more UAVs the percent return for each one significantly decreases.

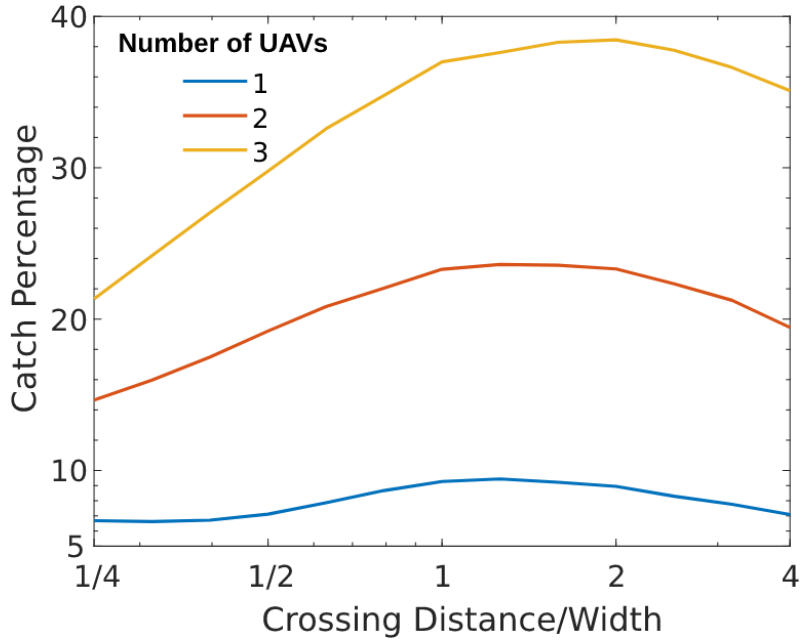

Figure 9: Catch Percentage versus Distance/Width Ratio for different numbers of UAVs.

Figure 9 shows catch percentage versus crossing distance to width for different numbers of UAVs. The property is 20 km^2 rectangle with 15% bush coverage. The poacher is attempting to cross in one direction; the other direction is the width, along which the UAVs transect. The figure shows the strong influence of property shape on catch percentage. As shown, the probability of detecting the poacher decreases when the poachers have a short crossing distance. The optimal positioning seems to be a crossing distance that is slightly larger than the width.

Summary and Conclusions for chapter 3, *The Roles of UAS & Domain Expertise in the Deployment of UAS within Organizations*, are provided in the chapter 4.

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CHAPTER 4

Summary and Conclusions

This dissertation developed a methodology for deploying UAS into organizations. The methodology was described by a process of six evolving steps encompassed by three stages (Fig. 1, Ch. 3.). As described, the early stages, previously called the "fuzzy front end," are the most critical. At this stage, one must properly set up the problem and incorporate both UAS experts and organizational experts to set up and manage the deployment process. Three aspects of the deployment are of particular importance – system reliability, its evolutionary nature, and the UAS/domain interface. When going through the process, which includes implementation in the field to create an evolving understanding of the inner working of the proposed system, the importance of these aspects becomes that much more evident.

One often discusses reliability together with cost and performance, wherein reliability poses a dilemma to the engineer because it is typically at the expense of the other two. However, in the context of deploying UAS, the UAS tends to be a lower cost alternative in which increased reliability translates into lower costs and improved performance. In the context of implementing new technology, previous research supports that reliability can be a driving factor. Querbes and Frenken (2018) described integrated product architectures, such as those described in this article. As they explained, sometimes these efforts require more centralized organization design with few options for outsourcing. Without the ability to outsource, organizations need either technical assistance from within the organization for complex operation and maintenance, or they need to have highly robust system within the organization that has sufficiently simple operation and maintenance such they do not require highly trained employees. The latter became preferred

when the advanced systems were too complicated for regular operation and repair without intervention from designers or significant training. This included pilot procedures such as flight path planning, operation including takeoff and landing, as well as maintenance including pre-flight testing and repair. Human resource plays a vital role in this whereby the less skilled the operator is with UAVs the more robust the system needs to be. However, given that one intends for the end-user to be within the organization, the likeliness that they would be highly skilled in UAVs would coincidental.

One designs the entire process of deployment within an organization around maintaining the highest level of reliability possible. The intent is for the system to function seamlessly within the organization. Anecdotally, the author of this article observed a good number of aerial systems developed within organizations that sit by the wayside because of excessive repair costs, excessively complicated high-tech solutions, and inadequate service support. The robust system gives the ability to accommodate failure including having back up measures. The UAS expert should be picking the solution away from the risk boundaries of cost and performance, which is where the highest level of reliability lies. As previously mentioned in the article, when the system becomes less reliable, the boundary is pushed, and things quickly become more expensive due to increased cost for more people, expertise, and components.

Like reliability, the evolutionary nature of deployment is a critical aspect. In general, it is well known that product development is iterative. Deployment is evolutionary and driven by in-house leadership. Merging in-house expertise and new non-in-house expertise is an important piece that takes on a unique evolutionary form. Organizational leaders should never overlook this aspect. They must expect the endeavor to evolve – for the knowledge base to grow before reaching a final useful form. There is an exceptionally low likelihood that developers could create a finished

product on the first iteration. They must allow ample time and iterations to take place to understand the issues. As was seen in both the aerial counting and anti-poaching systems, the developers had to understand deeply the interconnectedness of an extensive list of variables including both UAS and domain attributes.

The final and arguably most important aspect of deployment is the interface between the two knowledge bases – UAS and organizational. Having an expert in one area is easy but finding one in both is not. The organization drives the need for the problem at hand while the UAS solves the problem at hand. It seems rather intuitive once its stated, but often the problem is seemingly simple with buried complexity in the details that only the experts from each of the domain understand. Therefore, getting the two knowledge bases together early on and letting them stay together throughout the process is critical. Because of the evolutionary nature of the deployment problem and the need for system reliability, minimizing wasteful time and mitigating risk requires sufficient knowledge of the complete system, which can only be fully realized with participation of both sides. The essential knowledge that is lacking lies at the interface of the two knowledge bases.

This leads to two types of individuals within the organization who will take over the execution of the system after the deployment phase is complete. We shall refer to them as system experts and operators. The system experts are those who entered the process at the beginning, who understand the evolution of the system and its components. It is important to have more than one system expert, so the system does not rely on that one individual. The experts oversee maintaining the reliability of the system, which includes the ability to update the system to meet changing demands. These experts are also the ones who maintain the system, its components, and oversee operator training. The operators are those who are less skilled and easily trained for

repeated tasks. One needs them during the deployment process, too, if for no other reason than to understand capabilities, operator numbers, and training protocols for after the deployment is complete.

The UAS developer must always keep in mind, that even when all aspects of deployment are closely followed, there is no guarantee to success. Bringing in domain experts early and having them work closely throughout the process as discussed can help both in areas of replacement and supplemental technologies. These experts can help create a pathway for the new technology to develop more seamlessly through a multitude of ways, from battling stigmas to honing technologies to best fit the task. Understanding how low reliability can drive up operational costs and fuel frustrations within organizations is also critical to the process, similar to the evolutionary nature and its impacts. These concepts are emphasized in research such as when Ahmed, Wallace, and Blessing (2003) showed that experienced designer used particular *design strategies,* often minimizing iterations, compared to the novice that tended to use a *trial-and-error* strategy. When these iteration numbers get high and the system reliability is low, organizations instinctively start losing interest in the system from high cost and low performance. Additionally, the aspect of modelling aids by gaining insight from grasping the underlying architecture of the problem through the encoding process and identifying the inferences of the system through the decoding process. While all of these considerations are critical to a successful deployment, the developer must always remember that the world is chaotic and there are no guarantees to achieving success, only ways to improve one's odds to give the deployment a fighting chance.

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